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The Impact of Socioeconomic Status on 30-Day Hospital Readmissions in South Carolina

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THE IMPACT OF SOCIOECONOMIC STATUS ON 30-DAY HOSPITAL READMISSIONS IN SOUTH CAROLINA

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ABSTRACT

The current method for calculating excess hospital readmission penalties does not incorporate measures of socioeconomic status, thereby leaving nonprofit teaching and safety net hospitals vulnerable to financial reimbursement penalties due to exogenously determined heterogeneous patient populations. The literature has shown that socioeconomically disadvantaged groups are readmitted to nonprofit teaching hospital's in higher proportions than more advantaged groups. Increased readmission to nonprofit teaching hospitals has been linked with cost shifting from those unable to pay to those with the ability to pay for medical care. Therefore, a new method for determining hospital excess readmission penalties is needed to reduce the incentive of cost shifting and penalize underperforming hospitals in a more justifiable way.

The two objectives of this research are to demonstrate the differences among hospital readmission rates by hospital type, and to demonstrate how the current Hospital Readmission Reduction program penalizes nonprofit teaching hospitals for excess readmissions as a result of their exogenous patient mix. A proposed method of adjusting excess readmission penalty determination uses patient insurance status to proxy for socioeconomic status. Hospitals are then grouped into quintiles of similar distributions based on patient mix. The proposed method of calculating excess readmission penalties is applied to a database of hospital claims for acute myocardial infarction (AMI) patients in the state of South Carolina. Results of the proposed method are then compared to results from the existing Centers for Medicare and Medicaid Services (CMS) method of calculating excess readmission penalties. The collected empirical data is subsequently

used to construct bootstrapped samples to re-estimate excess readmission penalty. The bootstrapped analysis showed the difference in same hospital readmission penalties between the two methods resulted in a 1.12% revenue reduction for nonprofit teaching hospitals and 0.22% reduction for non-teaching hospitals. As a result, controlling for hospital patient characteristics caused by exogenous patient mix is likely to reduce the degree of hospital cost shifting to private payers.

DEDICATION

This dissertation is dedicated to the crazy ones.

The misfits. The rebels. The trouble makers. The round pegs in square holes. The ones who see things differently. They're not fond of rules and they have no respect for the status quo. You can quote them, disagree with them, glorify or vilify them. But the only thing you can't do is ignore them. Because they change things. They invent. They imagine. They heal. They explore. They create. They inspire. They push the human race forward. Maybe they have to be crazy. How else can you stare at an empty canvas and see a work of art? Or sit in silence and hear a song that's never been written? Or gaze at a red planet and see a laboratory on wheels? While some see them as the crazy ones, others see genius. Because the people who are crazy enough to think they can change the world, are the ones who do.

— Paraphrased from Rob Siltanen's "The Crazy Ones"

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To all of those in the former Applied Economics and Statistics Department at Clemson University, I wish you well, because it is you who will make positive changes in the world.

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CHAPTER I

INTRODUCTION

Healthcare policy reform is a complex and multifaceted problem that has plagued the United States for decades. The most recent healthcare policy reform is The Patient Protection and Affordable Care Act of 2010 (PPACA), which was signed into law on March 23, 2010. Originally passed to provide healthcare coverage to most Americans, the law is comprised of several smaller pieces of legislation to reform healthcare policy (Cannon, 2013). The intent of the law is to simultaneously improve health care quality and lower the cost of doing so nationwide. One important facet of this legislation is The Hospital Readmissions Reduction Program (HRRP). Hospital Readmissions within 30 days of a previous hospital admission have been shown to be a costly and undesired healthcare outcome (Nagasako et al. 2014, Jenks et. al 2009). Higher patient cost result from unplanned readmissions caused by misaligned incentives whereby a hospital receives compensation through Medicare reimbursements for the quality of care initially provided by a hospital. Prior to HRRP hospitals were effectively incentivized by the volume of patients rather than the quality of care provided. HRRP aims to improve the quality of care and lower costs by requiring hospitals to minimize the probability of readmission.

Established by section 3025 of the PPACA to improve the quality of care to the Medicare population, HRRP assesses penalties in the form of reduced reimbursement payments to hospitals with ‘excessive’ readmissions. The HRRP was implemented on October 1, 2012 by calculating excess readmissions ratios over a 3-year period for three diagnostic conditions, acute myocardial infarction (AMI), heart failure, and pneumonia. The law was further expanded to include exacerbations of chronic obstructive pulmonary disease, total knee and total hip arthroplasty in 2015. To determine excess readmissions, the program compares each individual hospital readmission rate to the national readmission rate calculated by the Centers for Medicare and Medicaid Services (CMS). Through a proprietary algorithm, CMS includes hospital and patient level variables to set an acceptable baseline readmission rate for each condition to which all hospitals are compared. Any hospital deemed to have a readmission rate in excess of the accepted readmission rate is penalized based on the ratio of excess readmissions to the accepted readmission rate. These excess readmission ratios provide the foundation for determining penalties in the form of a payment adjustment factor applied to Medicare reimbursement.

In the first year of this program, nearly two thirds of US hospitals received penalties for having readmissions rates above the CMS threshold rate. This resulted in 2,225 hospitals receiving total penalties of roughly $280 million in the form of reduced Medicare reimbursements (Williams 2013). In percentage terms, the penalties were capped at a maximum of a 2% reduction in a hospital's Medicare reimbursement in 2014 and a 3% reduction in 2015. Since 2012, there have been improvements in condition-adjusted readmissions rates and associated reimbursement penalties, with a decrease in the average penalty of 0.42% to 0.38% reduction in Medicare reimbursement (Rau 2013, MEDPAC 2013). Despite the marginal improvements as a result of HRRP, the legislation has a significant drawback by treating all hospitals as one homogenous group.

Many of the 2,225 hospitals are penalized for exogenous reasons outside their control as reported in the readmissions literature (Joynt, Jha 2013, Philbin et al., 2001). The primary driver of excess readmissions among larger teaching and safety net hospitals is the greater percentage of poor patients readmitted than patients of higher socioeconomic class (Kamerow, 2013, Lewin et al. 2000). Socioeconomic status is currently not taken into account when calculating excess readmissions rates, and many argue it should be included (Mueller et al. 2013, and Shahian et al. 2012, Philbin et al 2001, Shimizu et al. 2014). As these authors note, lower socioeconomic status increases the likelihood of readmission due to patients having less access to care, non-compliance to physician orders, and lower nutritional status, among many other reasons.

Teaching hospital's provide post graduate medical education to physicians, nurses and other medical professionals. Teaching hospitals are typically affiliated with a medical school or a university, and are closely tied to state and federal government through subsidies for medical student and medical resident education. In contrast, safety net hospitals provide care to large proportions of low-income, uninsured, or vulnerable patients. Many of these patients are unwilling or unable to pay for hospital services. Hospitals providing uncompensated care receive federal funding to cover these costs in much greater proportion to total revenue than non-safety net hospitals. Moreover, some teaching hospitals may also serve as safety net hospitals.

The key is to understand the relation between hospital type, patient socioeconomic status and hospital readmission rate. Outside of true emergency cases, some hospitals can refuse care to patients due to inability to pay. Safety net hospitals cannot refuse patients, and thereby often receive poor patients in higher proportions (Lewin et al. 2000). Another common characteristic is safety net hospitals are nonprofit institutions, and many teaching hospitals are also nonprofit. As to be discussed, nonprofit and for-profit hospitals have different objectives in terms of profit motive and importance of "prestige."

The Yale New Haven Health Services Corporation (YNHHSC), which provides analytical support to CMS and helped develop the current standards for the HRRP, explains the current rational for not including socioeconomic status when calculating excess readmissions:

> *"The measures also do not adjust for socioeconomic status because the association between socioeconomic status and health outcomes can be due, in part, to differences in the quality of healthcare groups of patients with varying socioeconomic status receive. Risk adjusting for socioeconomic status could also mask important disparities and minimize incentives to improve outcomes for vulnerable populations (page 12)."*

Nagasako et al. outline the argument well stating that the current policy, which excludes socioeconomic status, is maintianed ..."in order to maintain the visibility of differences in health outcomes for groups with different socioeconomic status characteristics (2014, page 787)." However, Nagasako et al. also note that there is a strong need to control for socioeconomic status factors "...to avoid disproportionately penalizing hospitals that care for a large number of patients from disadvantaged backgrounds and communities (2014, page 787)." Furthermore, Shimizu et al. find that the current standard of assessing hospital readmissions as an indicator of medical care quality is inadequate because it is applied irrespective of the patient populations served at hospitals throughout the country (Shimizu et al., 2014).

Joynt and Jha were among the first to expand the literature by reporting differences in Medicare reimbursement penalties stratified by hospital characteristics. They found that larger hospitals (>400 beds) received greater penalties than their smaller counterparts (<200 beds). Joynt and Jha showed that 40% of large hospitals were highly penalized compared to 28% of small hospitals. Highly penalized is considered a Medicare reimbursement reduction penalty above 0.72%, and a low penalty is less than a 0.15% reimbursement reduction. Additionally, major teaching hospitals are more likely to be highly penalized (44%) than non-teaching hospitals (33%) based on adjusted odds ratios from a multinomial logistic regression (P<0.001) (Joynt, Jha 2013). The evidence suggests that these differences are due in large part to socioeconomic factors as well as the greater proportion of medically complex cases larger teaching hospitals encounter, as compared to smaller non-teaching hospitals. Joynt and Jha clearly show that the level of Medicare reimbursement penalties are correlated with socioeconomic status. The authors provide adjusted odds ratios demonstrating that major teaching hospitals, which serve a more socioeconomically disadvantaged population, are more likely to be highly penalized (above average penalties) than non-teaching hospitals (44% versus 33%) and less likely to not be penalized than non-teaching hospitals (19% versus 35%, respectively). Additionally, Joynt and Jha found that safety-net hospitals are also more likely to be highly penalized than non-safety-net hospitals (44% versus 30%)   This result supports the hypothesis that lower socioeconomic status is often associated with increased medical complexity, and highly complex medical cases are admitted to teaching and safety net hospitals in a higher proportion relative to other hospital types (Philbin et al., 2001). Thus, teaching and safety net hospitals are likely to have a higher readmission rate.

Differences in patient populations among teaching versus non-teaching hospitals has been understood for decades but are now especially problematic and relevant due to the penalties associated with HRRP and PPACA. In 2001, Philbin et al. analyzed socioeconomic status as a risk factor for hospital readmission, following previous admission for heart failure. They found that after adjusting for other confounding factors, lower income is a positive predictor of readmission risk based on a statistically significant difference in the proportion of readmissions between the highest and lowest income quartiles using a Mantel-Haenszel chi-squared test ($P<0.0001$) (Philbin et al., 2001). More recently, studies assessing hospital care quality have shown that major teaching hospitals have lower mortality rates but higher readmission rates (Shahian 2012, Meuller 2013).

The emphasis on the quality of care provided by hospitals is a direct result of the PPACA, and is beginning to positively impact the U.S. health care industry by insuring more people. However, adjustments may be needed to ensure the longevity and continued improvement of the PPACA. Based on the cited literature, some of these program adjustments focus on the use of the HRRP to determine hospital quality in the changing healthcare industry. One of the primary policy changes being considered is incorporation of socioeconomic status into the excess readmission calculation.

In a report to Congress in June of 2013, the Medicare Payment Advisory Commission (MEDPAC) proposed several changes to the structure of HRRP (2013). One proposed change is to group hospitals based on the proportion of poor patients they serve and then calculate benchmark readmission rates of the "within" group average to which they will be compared. This proposed change is not a direct risk adjustment for socioeconomic status yet it functions in a similar way.

Many of the changes proposed by MEDPAC focus on the imbalance of incidence and magnitude of penalties for major teaching hospitals. MEDPAC documents that major teaching hospitals have received the highest average penalty, a 0.45% reduction in 2014 Medicare reimbursements, and also have the highest share of hospitals receiving the maximum 2% penalty relative to other hospital classifications. These differences might be explained by the federal obligation that teaching hospitals treat and care for the more disadvantaged patient groups. Until recently, such teaching hospitals received reimbursements through disproportionate share hospital (DSH) payments to compensate for the uninsured care they provide. The commission noted that major teaching hospitals receiving the highest penalties are also the hospitals receiving higher DSH payments. DSH payments are designed to compensate hospitals for the care and treatment of uninsured patients. However, at the time of MEDPAC's report, there was a legal and political debate nationwide which would confound the availability of future DHS payments to large teaching hospitals.

When the PPACA was signed into law on March 23, 2010, the constitutionality of various aspects of the PPACA was challenged by the Supreme Court of the United States in National Federation of Independent Business versus Sebelius, 2012. In their ruling on June 28, 2012, the Court declared that most of the components of the PPACA were constitutional except for the federal requirement that all states expand Medicaid eligibility to 138% of the federal poverty level. The court ruled that legislative change is a decision left up to the states. (The same legal situation as prior to the PPACA, where the eligibility requirement was left to each state, thereby resulting in highly variable Medicaid eligibility requirements nationwide.) The objective of nationally standardized Medicaid eligibility among all states is just one component of the PPACA meant to work in conjunction with the federal reduction in DSH payments. Under the original concept, no problem was anticipated because all states would have expanded Medicaid eligibility under the same rule, thereby providing access to health insurance for the poorest segment of the population. However, the Supreme Court ruling created the possibility of a large gap in health insurance coverage for the most economically disadvantaged people in states voting to not expand Medicaid eligibility. Theoretically, if states expanded Medicaid eligibility in conjunction with all other requirements of the PPACA, there would be few gaps in insurance coverage thereby rendering DSH payments almost unnecessary. However, in states that forgo the "option" to expand Medicaid eligibility, a gap of uninsured socioeconomically disadvantaged people will remain. Further compounding the coverage issue is the fact that when this population receives care from hospitals legally required to treat them, the hospital will no longer be reimbursed for their care. Consequently, when this same population is readmitted, the hospital will have to pay for their treatment and might be subject to losing a portion of their Medicare reimbursement for the excessive readmission.

In 2013, Nikki Haley, the governor of South Carolina (SC), vowed not to expand Medicaid Eligibility to South Carolinians. Her decision has resulted in an insurance coverage gap for some of the poorest people in SC, which has placed the burden of uncompensated care directly on larger teaching hospitals, which serve as safety net hospitals. The uninsured South Carolina population, which as Philbin et al. (2001) demonstrated, is more likely to be readmitted to the hospital, places the financial burden directly on teaching hospitals in two ways. First, the hospital must provide care to patients for which they are not completely reimbursed due to reduced DSH payments. Second, these patients contribute to a health center's marginal "excess" readmission rate, resulting in a Medicare reimbursement penalty and additional cost. The full ramifications of this outcome are not known. However, economic theory suggests hospitals might attempt to recover the deficit by shifting the cost of care from the uninsured to private payers. Another way to smooth the cost differential in SC teaching hospitals would be for the federal government reimbursement guidelines to include socioeconomic status as a factor in the risk-adjustment calculation.

Currently CMS does not include a measure of socioeconomic status in the calculation of excess readmissions and associated penalties. However, a growing body of literature clearly identifies socioeconomic status as a determining factor in hospital readmission (Philbin et.al, 2001, Shahian 2012, Meuller 2013). This literature clearly documents that low income patients have increasingly gone to nonprofit teaching and safety net hospitals for medical care (Lewin et al. 2000). These two issues in combination with the HRRP treating all hospitals as a homogenous group has resulted in an inappropriate standardized measure for calculating hospital Medicare reimbursement penalties and the degree of penalties they receive.

While it is important to document the differences between for-profit hospitals and nonprofit teaching hospitals, it is also important to consider the distribution and evolution of the two hospital types within the medical care market. Inherent to this market is the obligation to provide care to socioeconomically disadvantaged patients without an ability to pay, a role often assumed by nonprofit teaching hospitals. The act of providing uncompensated care can decrease revenues. It has been theorized that nonprofit hospitals may offset their revenue losses through gains in prestige associated with the provision of uncompensated care (Hirth 1997; Rosenman et al. 2000). An extension of Gary Becker's *"A Theory of Social Interaction"* is presented in Chapter III to demonstrate how the role of nonprofit hospitals is similar to the role of a "charitable" family member motivated by social acclaim through charitable actions (Becker, 1974). The notion of prestige optimization among nonprofit teaching hospitals is of primary importance in any discussion of medical care markets.

The objectives of this research are twofold. First, to illustrate the differences among hospital readmission rates by hospital type; second, to demonstrate how the current Hospital Readmission Reduction program penalizes nonprofit teaching hospitals for excess readmissions as a result of their patient mix. It is hypothesized that by developing a measure of excess hospital readmission that considers patient mix (patient characteristics), hospitals that serve a greater proportion of poor patients, who are often much sicker at admittance, will have a significant decrease in reimbursement penalty relative to the penalties they are now subject to as estimated under existing protocol.

A longitudinal data set of SC hospital visits is used to analyze the current method for calculating readmissions for Acute Myocardial Infarction (AMI). The difference in readmission rates between teaching and non-teaching hospitals is analyzed directly using chi-squared tests, and logistic regression analysis. Additionally a Cox Proportional Hazards model was used to test differences in hazard ratios between teaching and non-teaching hospitals. Readmission rates under the current and proposed MEDPAC methods are analyzed to assess differences in excess readmission penalties between the two methodologies. With the first method being the current HRRP method for assessing hospital readmissions, and the second method proposed by MEDPAC, that assesses excess readmissions by stratifying hospitals by the proportion of low income patients they serve. The magnitude of the estimated readmission penalty is a primary component of lost hospital revenue and can result in cost shifting. With reduced Medicare reimbursement as a result of excessive readmissions penalties stemming from patient mix, the revenue burden may be shifted to commercial insurance payers through higher hospital charges, which ultimately results in higher insurance premiums. Estimated readmissions penalties are compared under the current and proposed method to proxy for the potential degree of cost shifting as a result of differences in patient mix. Results from this comparison are used to determine which penalty structure is least influenced by socioeconomically disadvantaged patient populations. Previous research (White 2013, Morrisey 1993, 1994, 1996, Frakt 2010) has found that while cost shifting might exist as a result of reduced public payment, the degree of cost shifting is likely minor and primarily a result of market structure and hospital competition. Prior research also provides evidence against cost shifting and labels the increased cost phenomena as price discrimination. Regardless of the name placed on hospital behavior in response to reduced public payment, the fact remains that hospitals will attempt to recoup the reduced revenue from discrepancies in readmissions penalties stemming from diverse patient populations. These issues are discussed further in Chapter VI.

A review of the literature is presented in Chapter II. A theoretical model of cost shifting as a foundation for understanding the impact of socioeconomic status on readmissions penalties is presented in Chapter III. SC hospital data are presented in Chapter IV along with empirical discussion of the models being tested. Results are presented in Chapter V. Policy conclusions and research extensions are provided in Chapter VI.

CHAPTER II

LITERATURE REVIEW

The problem of hospital readmission has plagued hospitals long before the inception of Medicare's fee-for-service program. As discussed in Chapter I, care providers were previously incentivized by the volume of patients cared for rather than the quality of care provided to those patients. With the introduction of the Hospital Readmission Reduction Program (HRRP), the focus shifted away from herding patients in and out as quickly as possible towards a more quality centric focus. Historically, hospitals have been paid by Medicare for each patient based on diagnoses and procedures each time a patient is discharged from the hospital. Thus, if a patient returns to the hospital it begins the process anew, representing misaligned incentive structures as hospitals receive additional compensation for each readmittance. This protocol has exacerbated quality and cost concerns. The removal of this misaligned incentive through HRRP now requires hospitals to focus on the initial quality of care they provide to reduce the likelihood of an unplanned readmission. HRRP is proving to be an effective program with overall readmission rates falling to an average of 17.8% in 2012, from an average of 19.0% over the previous five years (Ness, 2013). However, there are many questions associated with the efficacy of the current readmission penalty structure. One main concern is the difference in case mix between non-teaching hospitals and larger teaching hospitals, which tend to serve the poorer and underinsured portion of the health care population (Kamerow, 2013).

Differences in hospitals often go further than just teaching or safety net status. In South Carolina for example, only a few hospitals treat severe heart attacks. Smaller hospitals transfer heart patients to larger hospitals, which can better serve them through more technologically advanced, resource-intensive care. Transferring patients places more pressure on teaching hospitals (which serve as treatment centers for severe cases) because if patients are readmitted for any reason it is the terminal hospital visit, which is charged with the readmission, not the initial hospital that transferred the patient. To gain an understanding of how diagnoses, timing, and other factors contribute to hospital readmissions, and how these factors vary among hospitals, it is necessary to review the literature.

Previous studies (Jenks 2009, Naylor 2004, Dharmarajan 2013) estimated the relationship between patient characteristics, including severity of illness at admission, and the time to readmission using Kaplan Meier curves, and Cox Proportional Hazard models. Jenks, Williams, and Coleman, analyzed the Medicare Provider Analysis and Review (MEDPAR) data file for all US Medicare fee-for-service patients from October 1, 2003 through September 30, 2004. The study population consisted of 11,855,702 patients deemed at risk for readmission, after removing records for patient death and transfers (2009). The cohort was analyzed for readmission at censored intervals of 30, 60, 90, 180, and 365 days for the five most common medical conditions and surgical procedures. The authors calculated the 30-day readmission rate, total readmission rate over the study period, as well as the readmission rate for the 10 most frequent readmitting conditions. The 30-day readmission rates for heart failure and pneumonia were 26.9%

and 20.1% respectively. The authors also calculated the national all condition 30-day readmission rate for the 2003 fiscal year to be 18.1%. Jenks, Williams, and Coleman identified the specific predictors of 30-day readmission. These predictors are (1) multiple prior hospitalizations over the study period; (2) an index length of stay (LOS) at least twice as long as average for an admission in the same diagnosis related group (DRG); (3) the disabled; (4) those receiving Supplemental Security Income (SSI) (indicative of poverty status); and (5) individuals older than 70 years of age.

While Jenks, Williams and Coleman focused on patient characteristics that contribute to readmission, much of the literature has focused on care transitions. The transition of care from a hospital setting to home requires education of the patient as well as the care takers on medication reconciliation and coordination of follow-up care. Research on hospital readmission (MEDPAC, 2007) illustrates that early hospital readmissions, within 7 days, are related to the quality of care received in the hospital. Conversely, the bulk of readmissions occurring after 7 days are related to issues surrounding discharge education and patient follow up (Stone, 2010). Readmission reduction programs focusing on care transition have been very successful and are now implemented in almost all hospitals nationwide as a result of HRRP (Ashton et al., Coleman et al., Hansen et al.).

One of the more prominent, successful interventions to improve care transition was studied in a randomized controlled trial done by Naylor et al. (2004). In this trial, the authors examined the effectiveness of using an advanced practice nurse (APN) trained specifically in heart failure to monitor patients with a heart failure admission, with the aim of reducing unnecessary readmissions. The authors recruited 239 patients admitted for heart failure and randomized them into either the intervention group, which received the care of an APN, or to a control group, which received routine care of the admitting hospital. The intervention group received three months of post hospitalization APN coordination between primary physician, pharmacists, and patients. The intervention group also had daily access to the APN as needed, including 24 hour follow up at the patient's home after leaving the hospital. The APN also fostered collaboration among the patient's therapists to inform the primary physician of progress and discuss needed changes in the care regimen. The effectiveness of APN coordination was analyzed by studying the differences in readmission rates between the control and intervention groups. The authors used Kaplan-Meier curves and Cox Proportional Hazard models to assess differences in timing and diagnosis of readmissions.

Study results found that fewer intervention group patients were readmitted within one year, as compared to the control group (44.9%, 55.4% respectively). Furthermore, the authors found improvements in reported quality of life as well as higher patient satisfaction ratings with the care provided by the intervention groups as compared to the control groups (Naylor et al., 2004). These improvements in readmission rates, quality of life, and patient satisfaction also resulted in an overall mean cost savings of intervention group of $4,845 per patient including the cost of training and compensating the APN's, as compared to traditional care in the control group. Here, costs represent the total cost to treat a patient through the entire course of their illness. The care coordination intervention was shown to be effective, both financially and clinically, in a controlled setting.

A more recent analysis of the diagnosis and timing of 30-day hospital readmissions was done by Dharmarajan et al (2013). They used Medicare fee-for-service claims from 2007-2009 to analyze diagnoses and timing for heart attacks (acute myocardial infarction, or AMI), heart failure, and pneumonia readmissions. These readmissions were categorized in ranges to analyze differences in diagnoses and readmission rates for date ranges including 0-3, 0-7, 0-15, 0-30, 4-7, 8-15, and 16-30 days. The authors used Kaplan-Meier survival curves censored at 30-days to analyze differences in time to readmission for 10 diagnosis categories. Cox proportional hazard models were estimated to determine the relation between patient characteristics and time to readmission by diagnosis group. However, the authors were unable to show any difference in readmission rates attributable to patient demographics, or time to readmission for hospitalizations of heart failure, heart attack, or presence of pneumonia.

If patients are readmitted at similar rates across age, sex, and race, what factors lead to differences in readmissions rates among hospitals? Joynt and Jha (2013) answer this question by analyzing differences in readmission rates and penalties by hospital type. Using HRRP data, they found that major teaching hospitals are more likely to be both penalized and more highly penalized when compared to non-teaching hospitals. Joynt and Jha mention that these "differences between hospitals are likely related to both case mix (medical complexity) and socioeconomic mix of the patient populations (page 343, 2013)." Incorporated into the readmissions estimates reported by Joynt and Jha are HRRP methods of risk adjusting to control for indicators of patient frailty (YNHHSC 2014). Therefore, if medical comorbidities (multiple chronic diseases affecting patient's health, ex. diabetes, hypertension, smoking) are controlled through risk adjustments, the resulting differences in readmissions pointed out by Joynt and Jha are due to differences in the socioeconomic populations at teaching versus non-teaching hospitals.

Mueller et al. (2013), and Shahian et al. (2012) test the hypothesis that teaching and non-teaching hospitals differ in quality and performance. Both studies concluded that teaching hospitals have lower mortality rates and higher readmissions rates than non-teaching hospitals. The higher readmission rate was surprising since teaching hospitals have more advanced clinical techniques. They explain this outcome by noting the high proportion of disadvantaged populations served by teaching hospitals are likely sicker when initially admitted.

Few papers have directly addressed the possible links between socioeconomic status and likelihood of readmission. Philbin et al. (2001) analyzed the socioeconomic status as a risk factor for readmission in heart failure patients in New York state hospitals. They found that patients from the lowest household income quartile had a significantly ($p < 0.0001$) higher percentage of readmission (23%) as compared to patients from the highest income quartile (20%). Furthermore, the authors point out that 65% of hospitalizations for lower income patients are in teaching hospitals, compared to 44% among higher income groups. Supporting this conclusion, Lindenauer et al. (2013) found a 1.5% increase in the risk of hospital readmission for every 5% increase in Gini coefficient. Stated another way, if the difference in mean income between the highest and lowest income quartile across patients increases by 5%, hospital readmissions would increase by 1.5%. Thus, as the disparity in patient incomes at a hospital grows, so does the readmission rate.

Shimizu et al. analyzed the factors related to readmission at a single teaching hospital (2014). The authors tracked all readmissions to their institution, Harbor-UCLA Medical Center from January through September of 2012. Harbor-UCLA Medical Center provides care to predominantly poor, uneducated, and very ill patients. They argue that their patient population is primarily responsible for their above US hospital average readmission rate. They conclude that that higher readmission rates at teaching hospitals are not related to the quality of care provided, but rather the characteristics of the patient population.

Thus, teaching hospitals are being penalized more for patient characteristics than quality of health care provided. Additional studies by Shimizu et al., Lindenauer et al., and Philbin et al. also support the hypothesis that readmissions rates at teaching hospitals are not a reflection of inadequate medical care, but rather the result of caring for a socioeconomically disadvantaged set of patients who often lack health insurance and tend to be sicker when admitted to the hospital. Aims to mitigate this specific issue are currently being debated and analyzed. In June of 2013 the Medicare Payment Advisory Committee (MEDPAC) issued a report to the US Congress with guidelines for refining the HRRP. One proposed refinement to HRRP is to explicitly recognize hospital readmission rates are positively correlated with their share of low-income patients (MEDPAC 2013).

The MEDPAC report notes the high readmission rate among teaching hospitals is directly tied to admitting low income patients who are more likely to be sicker upon admission. They further note that although The Centers for Medicaid and Medicare Services (CMS) risk adjust based on medical conditions such as increased age and other chronic conditions such as diabetes, they do not directly risk adjust based on socioeconomic status. Lower socioeconomic status is associated with increased incidence of these chronic conditions; however, it is not explicitly incorporated into CMS's algorithm assessing excess readmissions.

To examine the impact of socioeconomic status on readmission rates, hospitals were stratified into deciles by the proportion of Medicare patients who also qualified for Supplemental Security Income (SSI) (MEDPAC). SSI is a federal program for seniors and disabled individuals with incomes of less than $1,000 a month (MEDPAC). Analysis of readmission rates and penalties under the current HRRP scheme resulted in a strong monotonic relationship between the proportion of patients on SSI and readmission penalties (MEDPAC). While it may be difficult to dramatically reduce readmissions rates for hospitals treating the uninsured and poor, it may be possible to bring the rates closer to a national average using more comprehensive readmission measures. Hospitals that serve a large proportion of poor patients should see a downward shift in their excess readmission rate as a result of incorporating a proxy for socioeconomic status into the excess readmission calculation. The effect of this proposed policy change should more fairly treat hospitals that cater to the more socioeconomically disadvantaged.

This policy change provides a means to reduce penalties to teaching hospitals required to care for poorer, sicker patients. Evaluating hospitals in relation to their peers by share of care provided to low-income patients will provide an improved reference of comparison over the current comparison to the national average. For example, each hospital in a decile could be compared to the decile average, or group average, readmission rate to determine excess readmissions. Hospitals will still report their individual readmission rates, but when calculating penalties, hospitals will be compared to the performance of hospitals with similar economic patient profiles. This approach does not directly adjust for socioeconomic status. However, the group comparisons smooth the differences in patient mix among hospitals by controlling for income level. Furthermore, the reduction in excess readmissions penalties associated with this policy change will decrease the need for hospitals to shift the cost burden to other revenue sources.

In summary, this literature review addressed the issue of how socioeconomic status relates to excess readmissions. Dharmarajan et al. (2013) reveal that readmission rates are not influenced by demographic factors or timing; leaving differences in readmission rates to be explained by other factors that historically have not been considered, such as socioeconomic status. Furthermore, Joynt and Jha documented differences in excess readmission penalties among hospital types. They note that larger teaching hospitals are more likely to receive higher penalties than non-teaching hospitals (2013). Several authors explain the difference in readmission rates as a function of patient socioeconomic characteristics (Mueller et al. 2013, and Shahian et al. 2012, Philbin et al 2001, Shimizu et al. 2014). Utilizing this research, the MEDPAC report presents a solution that indirectly adjusts for hospital patient mix to more fairly calculate excess readmission penalties.

Building on this literature, an economic framework describing how hospitals are being unequally penalized due to variations in patient mixes is presented in the following chapter. The impact of socioeconomic status on readmission rates for AMI in South Carolina is calculated by hospital type using a model of the type described by the MEDPAC report. The estimated readmission rates are then used to determine the reduction in excess readmissions penalties, which would reduce the need for cost shifting at larger teaching hospitals. It is hypothesized that by controlling for the heterogeneity in patient mix among hospitals, a more equitable readmission penalty threshold standard can be developed that will reduce the need for hospitals to cost-shift.

CHAPTER III

CONCEPTUAL MODEL

I. Introduction

The literature discussed in the previous chapter focused on hospital readmissions. Building on that literature, this chapter considers the organization and structure of hospitals. There are three main types of hospitals in the healthcare market. They are for-profit, not-for-profit, and government owned. Although the share of for-profit hospitals has been growing (a 2.2% increase between 2006 and 2010 (AHA, 2012)), the revenue share of not-for-profit hospitals across all U.S. hospitals still exceed 50%. According to the 2015 American Hospital Association's annual review of Healthcare Statistics, 51.1% of U.S. hospitals are non-governmental not-for-profit, followed by 21.5% government owned, 18.6% for-profit, and the remaining 8.8% comprised by psychiatric, long-term care, and prison hospitals.(AHA, 2015).

This chapter presents a brief review of hospital structures, and discussion of the theory and behavior of these various hospital structures. A theoretical framework is then presented to better understand the current dynamics of hospital readmissions and the likely effect of revising the current metrics for assessing penalties for excess readmissions.

II. Unique Nature of Medical Markets

As Arrow (1963) stated "The first step in the analysis of the medical care market is the comparison between the actual market and the competitive model (pp 943-944)." The demand side of the health care market diverges from the traditional competitive model on the basis of uncertainty in demand for medical care, asymmetric information inherent in the physician patient relationship, and the requirement that hospitals provide emergent care to all patients without regard of ability to pay. Building on the latter of these traits, Arrow states "Departure from the profit motive is strikingly manifested by the overwhelming predominance of nonprofit over proprietary hospitals (p. 950)." Stated differently, traditional mechanisms (prices and quantities) dictating the allocation of goods and services to their most efficient outcomes are not always apparent in the structure of the medical care market due to institutional health care policies. In particular, healthcare providers and hospitals receive substantial subsidies for providing care to various groups deemed to be disadvantaged by lack of income or other factors. Such subsidies are absent in competitive neo-classical markets.

Hospital and the medical care markets are not fully subject to traditional neo-classical supply and demand characteristics. Instead of the traditional two party system of buyer and seller, the U.S. health care system is primarily a three party system. The three parties include the consumer, or patient, which receives the medical care, the insurance provider (private or public) that pays for the care, and the physician and hospital that provide the care. The three party system differs from traditional markets where the consumer and firm are directly linked.

The supply side of the health care markets is predominantly comprised of not-for-profit hospitals (51% in 2013). However, the diverse mix of patient needs and abilities to pay promoted an industry structure comprised of nonprofit, for-profit, and government owned hospitals. One explanation for this organizational structure is how hospitals arose to meet patient demands. As Horwitz (2005) explains, for-profit hospitals provide the most profitable services to patients that can pay. While government owned are more likely to offer unprofitable services, not-for-profit hospitals seek to balance the types of services offered (Horwitz, 2005). Horwitz notes a very important aspect of the behavior of nonprofit hospitals is the balance that must be maintained between treating patients able to pay with patients unable to pay. The diverse mix of patients at nonprofit hospitals is often a legal requirement for these hospitals to maintain their nonprofit status (Horwitz, 2015). The primary reason for this is that nonprofit hospitals receive governmental subsidies to adjust for the level of uncompensated care provided. The medical care market also diverges from traditional markets by the existence of demand for medical care at no cost being met with supply from nonprofit hospitals.

This intricate balance of nonprofit hospitals providing care to those with and without ability to pay raises interesting questions as to what nonprofit hospitals optimize. Nonprofit hospitals cannot simply maximize the quantity of profitable services provided because of the requirement to offer some quantity of unprofitable services (Horwitz, 2015). Thus, nonprofit hospitals often balance the value of prestige gained by providing care to underinsured and uninsured patients against the cost of the prestige (Chang and Jacobson, 2011). The notion of nonprofit hospitals motivated by prestige is revisited later in this chapter. First, it is important to review existing theories on nonprofit hospitals.

Provided that the market is comprised of different hospital structures, there is an extensive literature on what these varying hospital structures seek to optimize. For-profit hospitals can be expected to maximize the quantity of profitable services they provide. However, the optimization decisions for nonprofit hospitals are more complex and have been debated in the literature for decades (Newhouse, 1970, Chang and Jacobson, 2011).

An outline of the theories governing the goals of nonprofit hospitals (i.e., what they seek to maximize in an optimization framework), as provided by Horowitz and Nichols (2007), is reviewed here. In 1970, Newhouse proposed a model in which nonprofit institutions maximize output and prestige by providing additional health care services up to the point where marginal profit is zero. Newhouse cites prior studies that found hospitals operate optimally when they optimize the tradeoff between the quality of care provided and the number of patients they care for within a constrained operating budget (McNerney 1962, Long 1964).

Horowitz and Nichols then describe the role of a nonprofit hospital among other hospital types within a geographic region. They postulate that if "...neighbors [other hospitals] are driven more by profit motives, then the nonprofit will tend to treat less profitable patients (p. 4, 2007)." This assertion raises the important question of how nonprofit hospitals might behave given the diversity of hospital types within a region.

Weisebrod (2009), Salamon (1995), and Frank and Salkever (1991) all argue that nonprofit hospitals seek to maximize the total value of care in the presence of market failures (e.g. failure of competition through the three-party system, inadequate allocations of resources) and governmental failures (e.g. inadequate access to care). Thus, nonprofit hospitals are designed to satisfy unmet community health needs by providing services to patients who generate small, zero, or negative profits. To compensate for accepting and treating non-profitable patients, additional revenue is generated from more profitable services provided to patients with the ability to pay (directly or more often through insurance coverage), a practice termed "cost shifting." The conventional definition of cost shifting is provided by Dranove (1988) states that hospitals increase charges to privately insured patients to offset losses from Medicaid or Medicare reimbursements.

Pauly and Redisch (1973) argue that some nonprofit hospitals are for-profit hospitals in disguise, in that they maximize payments to "privileged employees" (hospital executives and physicians) as a proxy for maximizing profits. Profit maximization under a competitive equilibrium framework is Pareto efficient when social efficiency is maximized. Pareto efficiency is reached when it is impossible to improve the welfare of one without reducing the welfare of another (Varian 1984). The presence of cost shifting in medical care markets foregoes Pareto efficiency through a reduction in welfare of patients with the ability to pay for medical care as a result of covering the full cost of care for those without the ability to pay. As Arrow alluded to, prices and quantities in the medical care market are not always efficiently allocated. Compounding these issues, the inefficient outcome resulting from cost shifting might also be the result of the United State's three party healthcare system. The fact that hospitals can privately negotiate with insurance markets allows for distorted incentives where prices vary between providers and insurers for the same services (Wyden 2009, Hyman 2007). Because healthcare markets are not perfectly competitive, and thereby do not efficiently allocate resources to their highest valued use, there may be potential for Pareto improvements.

Other theoreticians argue the optimal healthcare policy objective function should optimize the additive sum of two health care agents. For example, Hirth (1997,1999) presents a model in which two types of hospitals, those that seek profits and those that do not, maximize collective hospital profit over both hospital types. Nonprofit status acts as a signal for increased quality and may drive low-quality for-profit hospitals out of the market. Hirth argues that low-quality for-profit hospitals attempt to exploit the market failure of asymmetric information based on the perception that high quality institutions charge higher prices because they provide superior care. The theory provided by Hirth argues that some patients are poorly informed on the quality of hospitals, resulting in 'information heterogeneity'. Hirth claims that poorly informed patients are potentially exploited by hospitals providing care of "quality which is not consistent with the price charged" (1997).   However, this theory is not useful for understanding hospital behavior in the presence of Medicare reimbursement penalties stemming from excess hospital readmissions because for-profit hospitals typically have lower readmission rates due to their ability to turn down care for poor and socioeconomically disadvantaged patients (Joynt and Jha 2013).

Hirth's key finding for our purpose is that hospitals (especially nonprofit hospitals) seek to maximize prestige, where prestige is an increasing function of patient numbers (Newhouse 1970). In particular, nonprofit hospitals maximize an objective function that includes altruistic motives along with the traditional profit motives. Two primary explanations exist for why a nonprofit hospital will maximize an objective function that includes prestige gained from altruistic care. First is the legal requirement of nonprofit hospitals to provide care to the uninsured (Horwitz, 2015). The second explanation is more theoretically ambiguous. Rosenman, Li, and Friesner (2000) posit that nonprofit hospitals optimize prestige through maximizing revenues subject to a constraint that it must cover cost. Doing so, with the given patient mix at nonprofit hospitals, requires optimization to occur in one of two ways. Either the nonprofit hospital provides higher private prices and lower public volumes, or lower private prices and higher public volumes in response to reduced public payments (Rosenman, Li, and Friesner 2000). This explanation demonstrates how nonprofit hospitals may shift costs in order to optimize prestige. Furthermore, it illustrates the ability of nonprofit hospitals to care for the uninsured (through increased prestige) while maintaining its ability to cover costs (through cost shifting). However, their assumption that a hospital can maximize revenue by changing multiple factors, volumes and prices to public and private payers, might inherently suggest that the hospital is acting as a for-profit rather than non-profit. Rosenman, Li, and Friesner's latter suggestion that hospitals may reduce private prices in response to reduced public payments falls directly in line with the work of Hay (1983) and Foster (1985) which state such behavior will be seen among for-profit hospitals. To further explore how prestige maximizing hospitals function in the market for medical care, the work done by Becker (1974) provides insight.

A reinterpretation of Gary Becker's (1974) seminal essay *"A Theory of Social Interactions"* provides a unique perspective on the prestige motive. Becker posits a "synthetic family" with a benevolent member providing charity "motivated by a desire to improve the general well-being of recipients" (p. 1083). The charitable member is assumed to be motivated by social acclaim. Stated another way, charitable members are motivated by social prestige gained from charitable actions. Becker continues by stating that charitable members "redistribute giving until everyone losing was fully compensated and everyone gaining was fully 'taxed' " (pp1083-1084). Becker concludes that in a family with a charitable giver, all members would try to maximize "family" opportunity and "family" consumption. The notion of "family" members working together implies a degree of social interaction, which, as Becker states, is ignored by traditional neoclassical theory. Moreover, Becker astutely notes: "Therefore, considerable ad hockery would be required if the 'conventional' approach were to explain the evidence on charitable giving that is more readily explained by an approach that includes social interactions" (p1085).

Expanding the scope of Becker's work, the "synthetic family" can be translated to the market for medical care where charitable members are interpreted as nonprofit hospitals. The nonprofit hospitals acting as charitable givers seek to maximize prestige through redistribution by providing uncompensated care to the uninsured and underinsured patients in need of medical care from excess revenues derived from privately insured patients. Stated more simply, nonprofit hospitals are able to provide "charity" care by shifting costs.

Extending Becker's work on "synthetic families" with a charitable giver did not originally translate to the medical care market. However, Bergstrom (1995) notes Becker borrowed concepts from the theory of the firm to explain production of his "synthetic family." Moreover, using Becker's theory of charitable giving in the setting of a "synthetic family" to describe the composition of hospitals in the market for medical care is a reasonable application of his original work. The modeling of the medical care market needs an analytic framework that allows hospitals to be viewed as agents who optimize prestige in the provision of uncompensated care to the underinsured and uninsured.

With the concept of nonprofit hospitals acting as prestige optimizers, a more complete theory of cost shifting is needed to explain redistribution in the setting of private and public payers comprising nonprofit hospital demand. Furthermore, a model explaining cost shifting as a function of the unique patient mix at nonprofit hospitals, coupled with the readmission discussion in Chapter II, is needed to understand the impact on hospital reimbursements.

III. Optimization of Nonprofit Hospital Model

The behavioral model developed here allows for the possibility of cost shifting. Hay (1983) and Foster (1985) assumed hospitals act as profit maximizing institutions where "marketing efforts" by the hospital are used to offset reduced government reimbursement. Consistent with prior discussion, it is assumed that hospitals do not act as a neo-classical profit maximizer (Arrow 1963, Varian 1984, Wyden 2009, Hyman 2007). Instead, hospitals act as price discriminators using cost-shifting to offset reductions in government reimbursements (Hadley and Feder 1985).

Dranvoe (1988) provides the foundation of the model used in this research to analyze the equity of current readmissions penalties. Dranove improves and builds upon the assumption that hospitals act as price discriminators through cost-shifting in the presence of reduced government reimbursements. He assumes that nonprofit hospitals serve two markets, *i* for private payers, and *j* for public payers. The hospital then chooses prices to maximize the following utility function

$$U = U\left(\pi^i(P^i, C^i) + \pi^j(P^j, C^j), Q^i(P^i), Q^j(P^j)\right) \qquad (3.1)$$

where P^i, P^j are prices charged to groups *i* and *j*; C^i, C^j are the costs to treat groups *i* and *j*; Q^i, Q^j represent the quantity of services provided to groups *i* and *j*; and π^i, π^j are the profits gained from the two groups respectively (*i* for private payers, and *j* for public payers). It is assumed that the hospital gains utility from profits in the form of monetary profits from private payers, $\frac{\partial U}{\partial \pi^i} > 0$, and altruistic utility, or prestige, by providing uncompensated care from public payers (consistent with Newhouse, Becker) or $\frac{\partial U}{\partial \pi^j} \geq 0$. Per unit medical care cost for the two groups are assumed to be identical, i.e., the cost is equal for resources used on a privately insured person versus a publicly insured person. Because nonprofit hospitals cannot deny service to the publicly insured population, Q^j is exogenous. P^j is also assumed to be fixed and exogenously determined by government payments. Collectively, these assumptions limit the choice of P^i as the sole means of utility maximization in 3.1. Note that for-profit or private hospitals may choose to refuse admittance to some individuals who could potentially be in Q^j, whereas all nonprofit hospitals are unable to decline care to any individual in group Q^i or Q^j. This assumption is reasonable because many private hospitals have the ability to turn away the uninsured, or patients with government (eg. Medicare, Medicaid) provided "public" insurance.

Nonprofit hospitals, which maximize utility gained from monetary profits from private payers and prestige from public payers, are forced to balance the patient mix in the presence of readmission penalties. The incentive to cost shift will remain greatest in states that have chosen to not expanded Medicaid eligibility because the proportion of patients in group Q^j will remain large. Ironically, many "opt-out" states serve large proportions of poor and indigent patients (larger proportion in group Q^j relative to Q^i) . Moreover, the pressure on nonprofit hospitals in such states to cost shift will increase as federal payments subsidizing the costs of uncompensated care are decreased over time.

Returning to Becker's concept of "family" and how nonprofit hospitals can be viewed as a charitable member of the "family". Nonprofit hospitals have the ability to set P^i at a utility maximizing level to redistribute potential revenue shortfalls in P^j as a result of less than full cost reimbursement by government (Becker, Sloan, 2000). Theoretically, this is likely when nonprofit hospital's reimbursements are reduced due to excess readmissions rates resulting from the high proportion of low income patients they care for. The Patient Protection and Affordable Care Act, defines readmission rates as excessive when a single hospital's readmission rate exceeds the national average. Because of the characteristics of their patients, nonprofit teaching hospitals often receive less than full reimbursements due to high readmission rates and the financial penalty associated with excess readmissions.

The first order condition sufficient for optimal P^i is satisfied where the marginal utility of a price change equals the marginal utility from the loss of output to the private markets (Dranove, 1988). The presence of cost shifting is demonstrated by total differentiating the first-order condition, and restricting profits to be positive and non-decreasing in the private market; thus $\frac{dP^i}{dP^j} < 0,$ which is cost shifting trade-off (Dranove, 1988; Sloan, 2000). Allowing both P^i and P^j to vary, a theoretical hospital *"...recovers from private paying patients some of the lost profits from government patients*" (Dranove, 1988). Or as Becker stated, the "charitable" nonprofit hospital seeks to maximize utility from profits and prestige by redistributing cost among private and public payers.

Public payers (coverage through Medicare or Medicaid) and indigents (who are unable to pay for medical services) tend to be sicker, on average, when admitted to a hospital and thus are more likely to be readmitted. Therefore, a hospital readmission penalty which does not account for the proportion of indigent and publicly insured patients admitted by certain hospitals will likely result in higher readmission penalties for hospitals serving a large proportion of indigent and publicly insured patients. To compensate for this revenue loss, these hospitals will attempt to shift costs to offset reduced reimbursement and gain prestige. Modifying the readmissions penalty algorithm to control for the proportion of poor patients admitted would effectively standardize the calculation of the critical readmission rate threshold to account for differences in patient socio-demographic characteristics. Recalling that nonprofit hospitals represent the majority of hospitals in the medical care market, it is appropriate to adjust the excess readmissions penalty algorithms to account for nonprofit hospitals' large proportion of publicly insured and uninsured patients.

Development of a more comprehensive readmissions penalty measure will level the hospital playing field and no longer put hospitals that serve a high proportion of low income patients at a competitive disadvantage. A change in the readmissions penalty algorithm can be achieved by comparing excess readmission rates to stratified group averages as expressed by the MEDPAC report (2013) where the stratified groups are comprised of hospitals with similar proportions of indigent and publicly insured patients. Reducing the readmissions penalty effectively increases the reimbursement to hospitals and reduces the incentive to shift cost to the private payers. It is hypothesized that grouping hospitals by proportions of indigent and publicly insured patients will result in a marginal decrease in reimbursement penalty attributable to differences in patient mix. The development of a more comprehensive measure of calculating excess hospital readmissions that controls for patient characteristics is necessary to accurately identify hospitals providing sub-standard care. The improved measure is needed before the important goal of achieving reductions in health care cost through reductions in patient readmissions can be realized by the Hospital Readmission Reduction Program (HRRP).

Traditionally, federal transfers called 'disproportionate share hospital payments' have limited cost shifting among hospitals serving a relatively large proportion of uninsured patients. As the Patient Protection and Affordable Care Act expands insurance coverage, there should be less uninsured patients and less uncompensated care provided by hospitals. However in 2012, the U.S. Supreme Court ruled the Medicaid expansion provision is a state option rather than a federal requirement. Thus, leaving large proportions of uninsured patients in states that "opt-out" of Medicaid expansion. The situation is complicated by reductions in payments to hospitals providing uncompensated care when readmission rates are excessive. For example, the Patient Protection and Affordable Care Act contains provisions to decrease federal healthcare payments to states in the form of reduced disproportionate share hospital payments each year from FY2014-

FY2020. Neuhausen et al. reported that even in a state (California) that did expand Medicaid eligibility, nonprofit hospitals were still confronted with a cost burden due to differences in the cost of uncompensated care and the reduced disproportionate share hospital payments (2014). Thus, states opting to expand their Medicaid program eligibility are confronted with a potential additional cost burden, but states that did not expand coverage are likely to face much larger cost burdens for uncompensated care.

Reductions in disproportionate share hospital payments do not account for states choosing to expand or not expand Medicaid eligibility. As a result, hospitals in "opt-out" expansion states are more likely to increase the degree of cost shifting through price discrimination than states where Medicaid eligibility has been expanded. Ultimately, until the United States moves to a single payer healthcare system, or all citizens are provided with some universal level of insurance, there will continue to be a mix of patients (based on ability to pay) that will necessitate the need for the nonprofit hospital structure. Furthermore, nonprofit hospitals will continue to act as a charitable "family" member providing healthcare to low income patients by redistributing costs among private, public, and uninsured patients. Therefore it is imperative to adjust the readmission penalty structures to account for these differences in patient mix.

CHAPTER IV

METHODS

This chapter presents the methods used to analyze the effect of patient mix on readmission rates among for-profit and nonprofit hospitals. The analysis will make use of South Carolina state-wide database for teaching and non-teaching hospitals maintained by the South Carolina Office of Research and Statistics. For the purposes of this analysis, teaching hospitals serve as a proxy for nonprofit hospitals, and non-teaching hospitals serve as a proxy for for-profit hospitals. The data can be stratified by hospital type and patient characteristics that allows for analysis of these factors on the probability of readmission.

The literature supports the need to stratify readmission analysis by hospital teaching status to more accurately understand differences in the hospital-type readmission rates (Joynt and Jha 2013, Shimizu 2014, Muller 2013, Shahian 2012). Stratification by hospital type is necessary to control for the influence of differences in patient mix and their hypothesized impact on pricing decisions. Chapter III outlined how prestige optimization at nonprofit, or teaching, hospitals may lead to cost shifting as a result of reduced public reimbursement for uncompensated care and increased readmissions rates.

The Centers for Medicare and Medicaid Services (CMS), a branch of the Department of Health and Human Services, currently assess readmission penalties by comparing readmission rates for a given hospital to the national average by multiple chronic disease conditions and major joint replacement categories. However, nonprofit teaching hospitals generally have a patient mix that is poorer, lacks health insurance and tends to be more ill than patients cared for in other hospitals. The current CMS penalty calculation ignores differences in hospital patient mix, which unfairly inflates the readmission rate of otherwise high quality nonprofit teaching hospitals.

Readmission rates are estimated for the South Carolina database using the current method of calculating excess readmissions. These results are then compared to the readmission rates based on the method proposed by the Medicare Payment Advisory Committee (MEDPAC, 2013), that indirectly incorporates a measure of socioeconomic status into excess readmission calculations. Comparing the two methods for calculating hospital readmission rates will shed light on inappropriateness of using a uniform procedural standard that does not consider hospital type and/or patient mix when calculating if a hospital has an excess readmission rate. Failure to control for patient mix can result in an unfairly high excess readmission rate for hospitals that have a high proportion of low income patients but provide very high quality patient care.

I. Data

To accurately analyze hospital readmissions, an extensive longitudinal data set that follows patients through entire episodes of chronic illnesses is required. A large patient population is also necessary to accurately estimate statistically significant differences between patient subgroups with the same medical condition. Hospital readmissions for chronic illnesses are analyzed in this study because they often require numerous hospital admissions to treat. Prior to 2015, chronic illnesses included in the CMS readmissions penalty calculations consisted of acute myocardial infarction (AMI), heart failure, and pneumonia. In 2015, readmissions penalties were expanded to include total knee and total hip arthroplasty, as well as exacerbations of chronic obstructive pulmonary disease.

With any disease or illness that may require hospital readmission the initial care level and subsequent patient management are of primary importance. The Hospital Readmissions Reduction Program (HRRP) is designed to improve the quality of care provided by hospitals during the initial admission including appropriate discharge education and out-patient care.

South Carolina hospital readmissions and the inherent quality of care provided is analyzed using data obtained from the South Carolina Office of Research and Statistics (ORS). The data set contains all payer hospital claims for all patients with any index admission for an acute heart attack (AMI), heart failure, or pneumonia from January 1, 2007 through December 31, 2011 in the state of South Carolina. All payer claims refer to complete hospitalizations for any individual regardless of insurance status. Only the data for patients with a hospital admission for a primary diagnosis of AMI during the study period are included in this study. For this set of patients, all other hospitalizations during the study period are also included in the data set. The demographic variables consist of age, race, and sex. Hospital level variables include size (measured by the number of hospital beds), trauma status (Level 1, 2...), teaching status (yes/no), and urban or rural location. Patient variables consist of primary diagnosis, admission source (emergency department, direct admit, transfer), admission date, discharge date, insurance payer, and length of stay. If a patient died during the study period, their data is excluded. These variables, and others included in the dataset, are fully described in Appendix C.

Several variables were created from the data set for analytical purposes, beginning with hospital readmissions. For AMI patients, the guidelines from CMS (Center For Medicare and Medicaid Services) and HRRP (Hospital Readmission Reduction Program), define a readmission as a subsequent hospitalization, to the same or different hospital, for any reason within 30 days of the initial admission with a primary diagnosis of an acute heart attack (AMI). If a patient is readmitted more than once within the 30-day period following an index hospitalization, only the first readmission is counted in the penalty calculation. This is an important distinction related to the chronic nature of AMI and frequency of hospitalizations. It is not uncommon for a patient to be admitted multiple times within 30-days of an initial AMI, hence the necessity for reducing such multiple readmissions as they are a burden on the healthcare system.

Binary variables were created to identify index hospitalizations, hospital transfers, and readmissions within 30 days. Index hospitalization is defined as the primary hospitalization where a patient is admitted and receives care. The primary hospitalization may be the hospital to which a patient was transferred. Hospital transfers are important to identify because if a patient is admitted at one hospital then transferred to another hospital, and the second hospital treats and discharges the patient, the second hospital is considered the index hospital. All readmissions are charged against the index hospital. In general, only certain hospitals in South Carolina have the ability to treat AMI patients. These patients are often transferred to teaching (nonprofit) hospitals for treatment. For example, a patient that suffers an acute heart attack in a rural area will be rushed to the emergency room of a small rural hospital to be stabilized. Once the patient is stabilized, he or she is subsequently transferred to a larger hospital with a better capability to treat them. The second hospital is the index hospital.

A continuous variable for the time (days) to readmission was also created. All variables and subsequent analyses were carried out using the statistical software R (version 3.0.2, r-group). The detailed computer code is provided in Appendix A. Once the data were arranged and organized properly, a series of iterative, multistep logical functions were created to determine if an individual patient was transferred after an admission for AMI (acute myocardial infarction). Similar logical functions were also created to determine if the patient was then readmitted to any hospital within 30 days of discharge from the previous admission, and the timing (days) between the previous discharge and subsequent readmission.

The variables created, as well as inclusion and exclusion criteria were followed as closely as possible to the CMS defined methods and guidelines (YNHHSC, 2014). CMS exclusion criteria for determining hospital readmissions include index hospitalization length of stay greater than 120 days and patients 18 years of age and older. For example, if a patient is less than 18 years of age on admission to the hospital, or if a patient is hospitalized longer than 120 days, they are excluded from the excess readmission calculation.

Additionally, it is not unusual for a patient to be readmitted multiple times within 30 days for various exacerbations stemming from the index AMI admission. In such situations, only the first readmission within 30 days, following an index admission for AMI is counted in the excess readmission calculation. Once the 30-day period is over, the readmission window will only start again if there is another index admission for AMI, and subsequent readmission. Additionally, to be counted, the patient must stay in the hospital at least 24 hrs, or overnight, otherwise the admission is excluded. Patients that arrive in the emergency department (ED) and are discharged, or patients admitted for observation are not considered as readmissions for penalty calculations. For example, a patient has an index admission for AMI and 7 days later arrives at the ED for dehydration, or shortness of breath. This patient is considered an "outpatient" unless he/she is admitted to a bed in the hospital. Only patients staying in the (ED) overnight, or for longer than 24 hours are considered a readmission for penalty calculations. It has been hypothesized (Zuckerman et al., 2016) that some hospitals attempt to circumvent possible readmission penalties by holding these patients in "observation." For hospitals, patients can be held in observation to monitor status without actually being admitted. This issue is further discussed in Chapter 6.

Another CMS defined exclusion criteria concerns patients transferred from another hospital. If a patient is transferred from another hospital, skilled nursing facility, or any other medical care source, the initial hospitalization is not counted as a readmission, only the index hospital that treats and discharges the patient is considered for a possible readmission penalty. Only patients with an inpatient hospital stay that arrived via emergency department or clinical referral (direct admit) are considered in this analysis.

For a hospital to be included in the HRRP they must have at least 25 index admissions for AMI in any three-year period. As a result, only 48 of South Carolina's 63 hospitals are represented in the AMI hospital population. (The identification code for hospitals with 25 or more index admissions and exclusion of those hospitals with fewer is provided in Appendix B).

Table 4.1 summarizes the demographic information for the AMI population used in this analysis. This table represents only the index hospitalizations and demographic information for an acute heart attack, AMI. The denominator for the reported percentages of gender, race, transfer and payment type in Table 4.1 and Table 4.2 is the total number of index hospitalizations for each respective groups. The final data set contains 13,793 AMI hospitalizations of which 12,875 are index AMI hospitalizations for 11,062 unique patients, with a median age of 55 years. The index AMI population is predominantly white (71.0%), male (68.3%), with commercial insurance (42.0%). Roughly 17.5% of the index AMI admissions in the study population resulted from a hospital transfer. The demographics are representative of the state of South Carolina and thus may not be reflective of national or other state averages. For payment type, the "Other" category is comprised of workers compensation, health maintenance organizations, health resources services administration programs, and managed care organizations.

Table 4.1 Patient Demographics for AMI Hospitalizations Only

No. AMI Hospitalizations	13,793
No. Index AMI Hospitalizations	12,875
No. Unique Patients	11,062
No. Hospitals	48
Age (years)	
Mean ± SD*	53.3 ± 8.0
Median(IQR**)	55 (48, 60)
Male, No. (%)	8,788 (68.3)
Race, No. (%)	
White	9,140 (71.0)
African-American	3,288 (25.5)
Other	447 (3.5)
Transfers, No. (%)	2,257 (17.5)
Payment Type, No. (%)	
Self Payment	2,540 (19.7)
Medicare	2,567 (19.9)
Medicaid	246 (1.9)
Commercial Insurance	5,404 (42.0)
Indigent	1,155 (9.0)
Other	963 (7.5)

Note: All values in parentheses are percentages other than median age that contains the interquartile range of 25th and 75th percentiles. *SD= Standard deviation, **IQR= interquartile range. N=12,875, total number of Index AMI admissions

As previously discussed, hospital readmission penalties impact nonprofit teaching hospitals more than non-teaching hospitals due to their patient mix. In this study, payment type is used to proxy for patient mix. Medicaid and indigent patients are considered to be low income patients. The AMI patient population was stratified by teaching and non-teaching hospitals, which serve as proxies for nonprofit and for-profit hospitals.

Table 4.2 reports the demographic characteristics for the South Carolina AMI patient population by hospital type. The number of hospitalizations far exceeds the number of patients because most AMI patients undergo multiple hospitalizations. All subsequent readmissions for patients originally admitted as an AMI patient are included, which include readmissions for any cause. The purpose of Table 4.2 is to describe the patients and hospitalizations among teaching and non-teaching hospitals for the AMI population. Both teaching and non-teaching AMI patients have similar average values for age, proportion of males, and distribution by race. Due to the large sample size all demographic variables are significantly different between hospital types (alpha level = 0.001), thus the p-values for the difference between hospital types are not reported.

A total of 5,431 index AMI hospitalizations were to teaching hospitals, compared to 7, 444 to non-teaching hospitals. Similar to the overall index population, both teaching and non-teaching index AMI admissions are comprised of predominantly white males with commercial insurance.

Table 4.2: Demographics for Patients With Any AMI Admission and All Other Hospitalizations During the Study Period Stratified by Teaching Status

	Teaching	Non-Teaching
No. All Hospitalizations	28,664	45,919
No. Index AMI Hospitalizations	5,431	7,444
No. Unique Patients	3,423	7,639
No. Hospitals	8	40
Age (years)		
Mean ± SD	53.2 ± 8.0	53.4 ± 8.5
Median(IQR)	54 (47, 60)	55 (46, 59)
Male, No. (%)	3,712 (68.3)	5,076 (68.2)
Race, No. (%)		
White	3,842 (70.7)	5,298 (71.2)
African-American	1,424 (26.2)	1,864 (25)
Other	165 (3.0)	282 (3.8)
Transfers, No. (%)	1,088 (20.0)	1,169 (15.7)
Payment Type, No. (%)		
Self Payment	923 (17.0)	1,617 (21.7)
Medicare	1,161 (21.4)	1,406 (18.9)
Medicaid	124 (2.3)	122 (1.6)
Commercial Ins.	2,139 (39.4)	3,265 (43.9)
Indigent	718 (13.2)	437 (5.9)
Other	366 (6.7)	597 (8.0)

Note: All values in parentheses are percentages other than median age that contains the interquartile range of 25th and 75th percentiles.
*SD= Standard deviation, **IQR= interquartile range, N=12,875, total number of Index AMI admissions

As expected, teaching hospitals have a higher rate of transfers than non-teaching hospitals (20.0% versus 15.7%). Furthermore, a key difference between teaching and non-teaching hospitals is the proportion of "Indigent" patients (13.2% versus 5.9%). The larger indigent population among teaching hospitals is because they are often nonprofit safety-net hospitals which receive federal funding reimbursing them for treating the poor. For-profit and non-teaching hospitals have the right to refuse care to those unable to pay. Teaching hospitals have a slightly higher percentage (2.3%) of Medicaid patients than non-teaching hospitals (1.6%) and Medicaid coverage is another indication of disadvantaged socioeconomic status.

The mix in patient types and severity of illness should be considered before proxying hospital quality using simple average readmission rates. Although readmission rates are adjusted for patients' comorbid conditions, the common measure for hospital quality is their average readmission rate relative to the national average, which ignores the hospital's patient composition (proportion of indigent, Medicare/Medicaid, commercial insurance, etc.) However, the literature shows (Shimizu 2014, Muller 2013, Shahian 2012), socioeconomically disadvantaged patients tend to be sicker and are among the most likely to be readmitted to the hospital. This discrepancy results in higher readmission rates for hospitals with a large proportion of indigent, and Medicaid patients relative to the national average proportion.

Penalizing nonprofit teaching hospitals for excessive readmissions attributable to uniquely different patient populations results in a flawed excess readmission rate calculation. Penalties imposed on hospitals having an excess readmission rate, in the form of reduced Medicare reimbursements, imposes a financial deficit on affected hospitals, which is often filled through cost shifting. Large teaching hospitals are nonprofit institutions that must cover costs while operating within the bounds of a fixed operating margin (Horowitz, Nichols 2009). To maintain budget and remain within an operating margin, hospitals negotiate pricing contracts with large insurance providers based on their expected patient mix (Horowitz, Nichols 2009) thereby shifting losses from Medicaid and indigent patients to privately insured patients.

The ability of a hospital to cost-shift is especially important for South Carolina's nonprofit teaching hospitals that price as if they are prestige optimizing, "charitable" family members in the medical care market (Becker, 1974; Hirth, 1999). A large indigent and Medicaid population exists in South Carolina. Therefore, the state's nonprofit hospitals have the burden of providing uncompensated care for this population, which is exacerbated by a flawed hospital readmission penalty calculation (Garfield et al., 2016). Even though nonprofit teaching hospitals may gain utility through prestige of treating the indigent population, it usually requires cost-shifting to cover cost.

Many solutions to this problem exist, perhaps the simplest being to expand Medicaid eligibility for all individuals up to 138% of the federal poverty level (as originally stated in the Patient Protection and Affordable Care Act of 2010), which would at least, to a degree, alleviate the problem. Medicaid does not typically cover the full-cost of patient care, but it does cover a significant portion (Barr, 2011). However, in 2015, South Carolina rejected this option. Another approach to reduce the incentive for hospitals to cost-shift is to redesign the formula that calculates excessive readmission and the subsequent Medicare reimbursement penalties. Accepting South Carolina's distribution of private, public, and uninsured patient as fixed, reductions in cost shifting behavior can be made by adopting a hospital readmission penalty structure similar to the one proposed by MEDPAC (2013).

The remainder of this chapter presents the methods for comparing nonprofit and for profit hospitals as a function of teaching status. The analytic foundation for comparing hospital readmission rates and penalties for excess readmissions is presented.

This information is then used to determine how the hospital readmission rate is affected by patient mix at each hospital type.

II. Statistical Methods

Using the patient demographic data and hospital level data, a standard logistic regression model and resulting odds ratios are calculated to determine how various demographic and hospital characteristics impact the likelihood of readmission. Readmission to the hospital is represented by ($Y_i = 1$), where $Y_i \sim bin(1, p)$, such that

$$p_i = \frac{exp(x_i^{'}\beta)}{1+ exp(x_i^{'}\beta)} \tag{4.1}$$

where $x_i'\beta$ is a vector of predictor variables (x_i') and associated parameters (β) that captures the impact of changes in x_i on Y_i (Green 2003). From equation 4.1, the likelihood function

$$\prod_{i=1}^{n} = p_i^{y_i}(1 - p_i)^{1-y_i} \tag{4.2}$$

is maximized where $p_i = e^{x_i'\beta}$when $Y_i = 1$, or $p_i = 1 - e^{x_i'\beta}$ when $Y_i = 0$. A forward step-wise regression technique was used to determine a model that can no longer be improved by adding an additional predictor variable (Hocking 1976). To interpret the impact of the independent predictor variables on the probability of hospital readmission the odds ratios are calculated using the estimated coefficients (β). Hosemer-Lemeshow test is used to determine goodness of fit for the logistic regression (Hosemer et al. 2013)

To evaluate the possible time sensitive reasons for hospital readmissions (and hence excessive or penalized readmissions from policy and cost viewpoints), a Cox

Proportional Hazards model is employed to estimate hazard ratios for the various socioeconomic factors influencing hospital readmission. The specification of the semi-parametric Cox Proportion Hazards model requires selecting a set of covariates that are multiplicatively related to the hazard ratio (Greene 2003). The baseline hazard rate represented by λ_0, is

$$\lambda(t_i) = \exp(x_i' \beta)\lambda_0(t_i). \tag{4.3}$$

Equation (4.3) allows for estimation of β for a vector of covariates. Now assume that K unique readmission times exist, $T_1, \ldots, T_K$, where t_i is a specific number of days and $T_K \leq 30$. Next assume R_K is the risk set containing all individuals who have not been readmitted in at least time T_K days, $\forall\ i \in\ R_K$, where $t_i \geq T_K$. The probability of a patient being readmitted at time T_K, given that exactly one patient has been readmitted at this time is

$$Prob[t_i = T_K | risk\ set_k] = \frac{e^{x_i'\beta}}{\sum_{j \epsilon R_K} e^{x_j'\beta}} \tag{4.4}$$

Equation (4.4) allows for the estimation of the partial likelihood function,

$$\ln L = \sum_{k=1}^{K} \left[x_k'\beta - \ln \sum_{j \epsilon R_K} e^{x_j'\beta} \right] \tag{4.5}$$

in which exactly one individual exits at each distinct time with no censored observations (Green 2003). However if multiple individuals m_k exit at distinct time intervals, then the log-likelihood function represents the sum of terms for each individual patient. Estimating the partial likelihood function in (4.5) allows for estimation of the hazard ratios for the covariates in relation to time to hospital readmission. The analysis presented here is a standard Cox Proportional Hazards model applied to the context of hospital readmissions (Greene 2003). Results of the hazard ratios, presented in Chapter V, estimate the effect of the demographic variables, teaching status, and insurance status have on the time to readmission.

The study data uses two approaches to estimate the excess readmission rate and subsequent reimbursement penalty. The first approach is suggested in the MEDPAC report and the second uses the current CMS policy. The MEDPAC report hypothesizes that the current CMS risk adjusting methodology, which does not include a socioeconomic adjustment for patient characteristics, excessively penalizes hospitals with an above average proportion of poor patients. The MEDPAC study found that low income is a more consistent predictor of hospital readmission than age, sex, or race. Therefore adjusting readmissions rates for income status should result in a more meaningful standardized comparison (MEDPAC, 2013). It is also hypothesized that a superior estimate for standardized hospital readmission average rates will reduce reimbursement penalties for teaching hospitals and thus, reduce the degree of cost shifting to privately insured patients.

The statewide data used for this study does not contain a measure of socioeconomic status. Thus to compare hospitals in a similar manner to the MEDPAC report, the data are stratified by the proportion of indigent and Medicaid patients a hospital serves. The MEDPAC report proxies socioeconomic status using the proportion of patients at each hospital on Supplemental Security Income (SSI), stratified into deciles, however that data is not available for this study. Thus, the proportion of poor (indigent and Medicaid) patients served by each hospital is used to proxy for socioeconomic status in this study. Each patient's "method of payment" is used to proxy for socioeconomic status. Poor patients are defined as patients who are either indigent (unable to pay) or patients on Medicaid, which is government subsidized health insurance coverage for unemployed and those with very low income. To calculate the proportion of poor patients a hospital serves, the sum of indigent and Medicare patients was divided by total hospital admissions in each hospital. Using a procedure similar to the MEDPAC report, Each of the 48 South Carolina hospitals in the AMI data set were then stratified into quintiles based on the proportion of poor patients they treated to create appropriate groups for analysis. Table 4.3 provides the quintiles, number of hospitals, and range of the proportions of poor patients served. These quintiles will serve as individual comparison groups, whereby each hospital's readmission rate will be compared to the quintile average, in addition to the statewide average under the original CMS protocol.

Table 4.3: Quintiles by Proportion of Poor Patients

Quintile	No. Hospitals	Proportion Poor Patients* (%)
1	9	4.74 - 7.52
2	9	7.69 - 9.49
3	10	9.57 - 11.15
4	10	11.31 - 15.64
5	10	15.68 - 21.55

* Ranges for the proportion of poor patients, calculated as the proportion of Indigent and Medicaid AMI patients served by the hospital during the study period.

The stratification of the 48 South Carolina hospitals into quintiles shown in Table 4.3 will serve as the basis of the group level comparison of readmission rates presented in the forest plots in Chapter V (Figures 5.2-5.6). While Tables 4.1 and 4.2 show rates of Indigent and Medicaid to be much lower than these proportions, it is important to note that these are the proportions of Indigent and Medicaid at any one specific hospital, which are then stratified into quintiles.

In the next chapter, a series of forest plots are constructed to analyze the overall and quintile hospital readmission rates. A hospital is determined to have 'excess readmissions' if the lower bound of the 95% confidence interval for its readmission rate is above the state-wide average (original CMS method), or quintile group average (MEDPAC, quintile level method). The quintile-level results are then compared to the average state-wide excess readmission rate. Table 4.3 reports the proportion of poor patients for the 48 hospitals across quintile groups.

The two procedures presented here are used to determine when a hospital readmission rate is excessive. By comparing two methods for determining excess readmission rates, light will be shed on the degree to which 'excess' readmissions are driven by the population share of low income patients a hospital cares for. The calculation of excess hospital readmissions as determined by the two approaches is a secondary outcome. The primary outcome is the amount of the penalty, which is a function of the estimated readmission rate. It is not the fact of being penalized that is of importance, but rather the amount of the penalty that can be hypothetically attributed to the proportion of poor patients a hospital serves. The dollar value penalty a hospital receives is a function of having an excess readmission rate and the difference between the hospitals estimated readmission rate and the reference readmission rate. When the reference rate is changed due to an alternative means of estimating excess readmission (state-wide readmission rate versus the quintile-level readmission rate) the dollar value of the penalty changes.

Due to the loss of independence by using each hospital's readmission data to estimate an single aggregate state-wide readmission rate to which each hospital was then compared to, additional analysis was conducted to decouple individual hospitals from the aggregate state-wide readmission rate. The loss of independence here is that the weighted average state-wide readmission rate is comprised of each of the 48 hospital's data, to which the individual hospitals are compared for penalty determination. Thereby making the aggregate state-wide average dependent upon each hospital's readmission data. To evaluate the empirical analysis, each of the 48 hospital's readmission rates were re-sampled with replacement 1,000 times using nonparametric bootstrapping methods[1]. The resulting 1,000 bootstrapped readmission rates were built using each hospital's sample size (the number of index AMI admissions), and the empirical readmission rate. Additionally, 95% confidence intervals were estimated for each of the 1,000 estimated readmission rates for all 48 hospitals. The bootstrapping process allows for analysis of the 48,000 bootstrapped hospital samples to be compared to 1,000 state-wide averages, as well as 5,000 quintile group averages (1,000 for each quintile) as a means of evaluating the empirical analysis. Sample code outlining these processes can be found in Appendix D. Creating 1,000 state-wide readmission rates for comparison was done to mitigate the loss of independence present in the empirical analysis.

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[1] R package "bootstrap"

[2] Note: "other insurance" category is comprised of workers compensation, health maintenance organizations, health resources services administration programs, and managed care organizations.

[3] The primary reason for using 5 years of data rather than 3 is because the data used in this study contains

While these bootstrapping techniques are built on the empirical data, the process allows for retesting the study hypothesis. Consistent with the initial hypothesis, the hypothesis tested with the boot-strapped samples is that the quintile method, which controls for patient socio-economic factors (income), will result in a lower excess readmission rate than using the state-wide average rate as the frame of reference for determining excess hospital readmission rates. Thus, the excess readmission penalty will be less with the quintile method. Testing the hypothesis using the 1,000 bootstrapped samples allows for a more robust analysis than if only the collected data set was used to empirically test the maintained hypothesis. If the resulting bootstrapped analysis reveals a similar pattern of readmission rates, and shows similar reduction in excess readmission related penalties from the state-wide average compared to the quintile level averages, then the empirical results can be accepted with greater confidence.

CHAPTER V

EMPIRICAL RESULTS

I. Introduction

An accurate calculation of a hospital's readmission rate is critical to the success of the Hospital Readmissions Reduction Program (HRRP). The hospital readmission rate determines whether or not a hospital has excess readmissions, and the degree to which the hospital is financially penalized. In fiscal year 2013, the maximum Medicare reimbursement penalty was 1% for excess readmissions. The maximum penalty was increased to 2% in fiscal year 2014 and further increased to 3% in 2015. The number of diagnostic categories subject to excess readmissions penalties has been increasing. In 2015, hospitals can be penalized for excess readmissions for patients with acute myocardial infarction (AMI), heart failure, pneumonia, chronic obstructive pulmonary disease, total knee arthroplasty, and total hip arthroplasty. With the potential for penalties being assessed in each of these categories, it is imperative to accurately determine a standard hospital readmission rate for each diagnostic category by controlling for patient characteristics.

Extensive discussion in prior chapters pertaining to differences in hospital structure and patient composition highlight the importance of these factors in estimating excess hospital readmission penalties. Chapter III provides insight into optimization decisions among for-profit and nonprofit hospitals and how these optimization decisions are driven by patient mix. Nonprofit hospitals care for higher proportions of Medicaid and indigent patients than for-profit hospitals, which indicate they incorporate prestige in their optimized decision. Here, prestige is a function of the quantity and quality of care provided to those without regard for ability to pay. The notion of prestige differs from optimization at for-profit hospitals that maximize profits as a function of increased patient numbers. The disparities in patient mix are documented in chapter IV for a sample of South Carolina hospitals that revealed a significantly higher proportion of indigent patients admitted to teaching hospitals than nonteaching hospitals (8.9% versus 3.2%). Incorporating a measure of patient composition into excess readmissions penalties may reduce cost shifting among nonprofit teaching hospitals.

To test this hypothesis, excess readmission rates are analyzed under the existing national average method as well as the method proposed in the MEDPAC (2013) report. The MEDPAC report represents the collaborative efforts of The Centers for Medicare and Medicaid Services (CMS) and the Yale New Haven Health Services Corporation to design an improved readmission measure for determining hospital quality (YNHHS, 2014). The following analysis adheres to these guidelines as closely as possible to accurately identify hospitals with excessive readmissions in the South Carolina data base.

II. Results

A logistic regression analysis was conducted to determine which demographic and hospital level factors influence the likelihood of readmission. The resulting odds ratios and 95% confidence intervals of the logistic regression are presented in Table 5.1. The Hosmer-Lemeshow test indicated that the logistic regression model is well calibrated and correctly specified (p-value=0.989).

The condition number (a diagnostic tool testing for the existence of multicollinearity, or high correlation between predictor variables) in the logistic regression is 15.64, which indicates the model does not suffer from multicollinearity among the independent variables. Multicollinearity in regression analysis can be a problem when strong correlation among predictor variables highly influences the coefficient estimates. In the logistic regression model presented in Table 5.1, age is not included in the model due to strong correlation with Medicare (correlation coefficient of 0.874). Including age in the regression results in a condition number of 712.3, indicating strong multicollinearity (any condition number greater than 30 is indicative of multicollinearity (Pesaran, 2015)). Running the two models side by side, one including age and one without, provides a comparison of the impacts of multicollinearity. R code for each regression is found in Appendix H. Removing the age variable eliminates multicollinearity while leaving coefficients of other predictor variables relatively unchanged; an indication that multicollinearity existed in the previous model, yet it had very little impact on the model as a whole. Additionally, while the coefficients and odds ratios were relatively unchanged the standard errors were shown to be reduced by removing the multicollinearity. A matrix of correlation coefficients among the independent variables in the logistic regression is presented in Appendix D.

Table 5.1 Odds Ratios and 95% Confidence Intervals for 30-Day AMI Readmissions

	Odds Ratio	95% Confidence Interval
Intercept*	0.1616	(0.1204, 0.2146)
Female*	1.1494	(1.0496, 1.2581)
Self-Payer	0.8898	(0.7379, 1.0765)
Medicare*	1.4586	(1.2182, 1.7531)
Medicaid*	1.4746	(1.0767, 2.0058)
Commercial Insurance	0.8889	(0.7485, 1.0604)
Indigent	1.0465	(0.8456, 1.2967)
White	1.0871	(0.8538, 1.4014)
African American	1.2652	(0.9854, 1.6433)
Teaching Hospital*	1.4015	(1.2849, 1.5284)

*Variables significant at alpha =0.05 include the intercept, female, Medicare, Medicaid, and teaching hospitals indicated by a 95% confidence interval not containing the value of one. N= 12,875, the number of Index AMI Hospitalizations

Results presented in Table 5.1 show that publicly funded Medicaid and Medicare patients are much more likely to be readmitted (47% and 46% more likely) than "other insurance" patients[2]. Females in South Carolina are 15% more likely than males to be readmitted to the hospital following an admission for AMI. Additionally, one of the most important statistical results is that patients at teaching hospitals are 40% more likely to be readmitted than patients at non-teaching hospitals. This result can be partly explained by the differences in the mix of insurance providers and severity of illness among patients cared for at teaching hospitals compared to non-teaching hospitals (Mueller et al. 2013, and Shahian et al. 2012, Philbin et al 2001, Shimizu et al. 2014). These findings set up the comparative analysis between teaching and non-teaching hospitals throughout the remainder of this chapter.

[2] Note: "other insurance" category is comprised of workers compensation, health maintenance organizations, health resources services administration programs, and managed care organizations.

A more comprehensive logistic regression model could either include hospital teaching status as random effect, or as an interaction term with Indigent and Medicaid. This might provide more evidence to support the hypothesis that the patient composition among teaching hospitals is associated with increased likelihood of readmissions. Furthermore, the Medicare variable could be stratified into 2 populations, the standard 65 and older population, and the less than 65 population with serious disabilities or comorbid health conditions.

Table 5.2 reports the overall hospital readmissions rates and timing (in days) to readmission for the 48 hospitals in the data set. Data represented in Table 5.2 show the crude number readmitted as well as the percentage readmission and time to readmission (measured in days). The focus of this table is a descriptive analysis of the readmitted population, and shows how readmission rates differ by gender, race, and insurance payment type, as well as how the time to readmission might differ among those categories.

Table 5.2: Index AMI Readmissions Rates and Timing for all South Carolina Hospitals

	N (Admitted)	Readmission (%)	Timing (days)
Overall	12,875	19.7	14.5 ± 8.8
Range Among Hospitals	-	2.6 - 28.2	0 - 30
Male	8,788	18.7	14.7 ± 8.7
Female	4,087	21.8	14.1 ± 8.9
Race			
White	9,140	18.8	14.5 ± 8.8
African-American	3,288	22.6	14.5 ± 8.7
Other	447	16.8	13.0 ± 9.0
Payment Type			
Self Payment	2,540	17.7	14.1 ± 8.6
Medicare	2,567	26.5	14.6 ± 8.9
Medicaid	246	28.5	13.2 ± 8.8
Commercial Insurance	5,404	17.1	14.7 ± 8.9
Indigent	1,155	20.3	14.4 ± 9.0
Other	963	18.5	14.0 ± 8.8

All timing values other than range are reported as Mean ± SD, in days.
N= 12,875, the number of Index AMI admissions.

Across all 48 hospitals, the arithmetic mean readmission rate for AMI patients is 19.7%, and individual hospital readmission rates range from 2.6 % to 28.2%. When stratified by gender, females are readmitted more frequently than men (21.8% versus 18.7%). African-Americans have the highest readmission rate at 22.6%, followed by whites at 18.8%, and all other race/ethnicity classes at 16.8%.

Insurance status provides an interesting breakdown of readmissions rates. The self-payer readmission rate and the commercial insurance readmission rate are the two lowest rates at 16.5% and 16.9%. Medicare patients have the second highest readmission rate of 25.9%, most likely because these patients are usually older and often seriously ill.

Patients receiving Medicare are usually 65 years of age or older, except for patients with certain disabilities, including end stage renal disease, Lou Gehrig's disease, and patients receiving Social Security Disability Insurance Payments, who receive coverage regardless of age (Barr, 2011). Medicaid patients are readmitted most frequently at 27.8%. Indigent patients have the third highest readmission rate of 20.1%. Medicaid patients and the indigent are poorer, often sicker patients with higher than average readmission rates. Medicaid and indigent patient status is used to proxy for low income socioeconomic status in this analysis.

Time to readmission was calculated to determine if there is a difference in time to readmission by payment type, where payment type is a proxy for patient mix. Average time to readmission across most groups is roughly 14 days, with the exception of Medicaid patients who are readmitted one day earlier on average.

Hospital-level readmissions rates and time to readmission across demographic groups for teaching and non-teaching hospitals are reported in Table 5.3. Pearson's chi-squared tests are used to determine differences in readmission rate between teaching hospitals and non-teaching hospitals across the demographic variables. Student's t-test are used to determine differences in time to readmission across the reported demographic variables. Any p-value < 0.05 is considered to be statistically significant. Similar to results regarding AMI readmissions, there is not a significant statistical difference between teaching and non-teaching hospitals with regard to the average number of days to readmission. Neither demographic nor insurance considerations affect the length of time to readmission between the two hospital types. This general result is further analyzed using the Cox Proportional Hazards model.

An example interpretation of Table 5.3, out of all Male index AMI admissions to teaching hospitals, 782, or 21.1% were readmitted. All other values can be interpreted in a similar manner.

Table 5.3: Percent Readmissions and Average Timing To Readmission for Teaching and Non-Teaching Hospitals Index AMI Hospitalizations

	Teaching (N=8)			Non-Teaching (N=40)			P-values	
	N (Admitted)	Readmission (%)	Timing (days)	N (Admitted)	Readmission (%)	Timing (days)	Readmission (%)	Timing (days)
Overall	5,431	22.2	14.4 ± 9.0	7,444	18.0	14.6 ± 8.6	< 0.001	0.346
Range Among Hospitals	-	13.2 - 24.2	0 - 30	-	2.6 - 28.2	0 - 30	-	-
Male	3,712	21.1	14.4 ± 9.0	5,076	16.5	14.9 ± 8.6	0.001	0.336
Female	1,719	24.2	14.0 ± 9.2	2,368	20.1	14.2 ± 8.6	< 0.001	0.710
Race								
White	3,842	21.4	14.5 ± 9.1	5,298	16.9	14.5 ± 8.6	<0.001	0.910
African-American	1,424	24.0	14.0 ± 8.8	1,864	21.5	15.0 ± 8.5	0.097	0.112
Other	165	20.0	12.6 ± 9.4	282	14.9	13.5 ± 9.0	0.207	0.576
Payment Type								
Self Payment	923	19.8	14.0 ± 8.8	1,617	16.5	14.2 ± 8.5	0.036	0.856
Medicare	1,161	27.6	14.3 ± 9.0	1,406	25.7	14.8 ± 8.7	0.302	0.529
Medicaid	124	37.1	13.9 ± 8.8	122	19.7	12.0 ± 9.0	0.004	0.382
Commercial Insurance	2,139	19.0	14.2 ± 9.1	3,265	15.9	15.1 ± 8.6	0.004	0.134
Indigent	718	23.4	14.9 ± 9.1	437	15.1	13.2 ± 8.8	< 0.001	0.194
Other	366	20.5	13.7 ± 9.5	597	17.3	14.0 ± 8.2	0.242	0.711

Note: "other insurance" category is comprised of workers compensation, health maintenance organizations, health resources services administration programs, and managed care organizations. N= 12,875, the number of Index AMI admissions, 5,431 at Teaching Hospitals, 7,444 at Non-Teaching Hospitals

Medicaid and indigent patients were readmitted in higher proportions with more variability in time to readmission than patients with other insurance providers as shown in Table 5.3. Table 5.3 also reveals that Medicaid (p-value=0.004) and indigent patients (p-value < 0.001) have higher readmission rate at teaching hospitals than non-teaching hospitals. Other forms of insurance payment, including commercial insurance, do not show significant differences in readmission rates between teaching and non-teaching hospitals. Differences in readmission rates for the Medicaid populations is roughly 17.4% (37.1%-19.7%), and 8.3% (23.4%-15.1%) for the indigent populations, compared to less than 5% for all other forms of insurance payment between teaching and non-teaching hospitals. The overall readmission rate is significantly higher at teaching hospitals (22.1%) than non-teaching hospitals (18.0%, p-value < 0.001). Based on the literature (Mueller 2013, Shahian 2012, Philbin 2001, Lindenauer 2013) and the analysis presented here, the difference in readmission rates between teaching and non-teaching hospitals is likely to be partially attributable to patient mix and not exclusively hospital quality.

The results in Table 5.3 support the hypothesis that exogenous differences in patient mix between nonprofit teaching hospitals and non-teaching hospitals influence the rate of readmission for a given illness. The dominant driver in the readmission rate difference between hospital types is likely attributable to the differences in patient mix between teaching versus non-teaching hospitals. Statistical support for this statement is found in the significant differences in readmission rates for the poorer patient classes (Medicaid, and indigent insurance provider) than patients in higher income classes. The limited number of hospitals studied, 8 teaching and 40 non-teaching, presents a statistical limitation which is addressed later in this chapter. The prior descriptive analysis presents a strong case to modify the current hospital penalty calculations for excess readmission rates fail to account for differences in exogenous patient mix.

Due to the similarity in timing of readmission across most demographic and teaching categories as presented in Tables 5.2 and 5.3, a Cox Proportional Hazards model was estimated to disentangle the relationship between demographic characteristics and time to patient readmission. The resulting hazard ratios and 95% confidence intervals for this analysis is presented in Table 5.4.

Table 5.4: Cox Proportional Hazards Results for Time to Readmission

	Hazard Ratio	95% Confidence Interval
Age	0.9964	(0.9914, 1.0014)
Male	0.9753	(0.8997, 1.0573)
White	0.9192	(0.7335, 1.152)
Black	0.9252	(0.7332, 1.1675)
Self Pay	0.9674	(0.8144, 1.1492)
Medicare	0.9442	(0.8012, 1.1128)
Medicaid	1.0469	(0.798, 1.3735)
Commercial Insurance	0.9074	(0.7746, 1.0629)
Indigent	0.9117	(0.7513, 1.1062)
Teaching Hospital	0.9840	(0.9099, 1.0642)

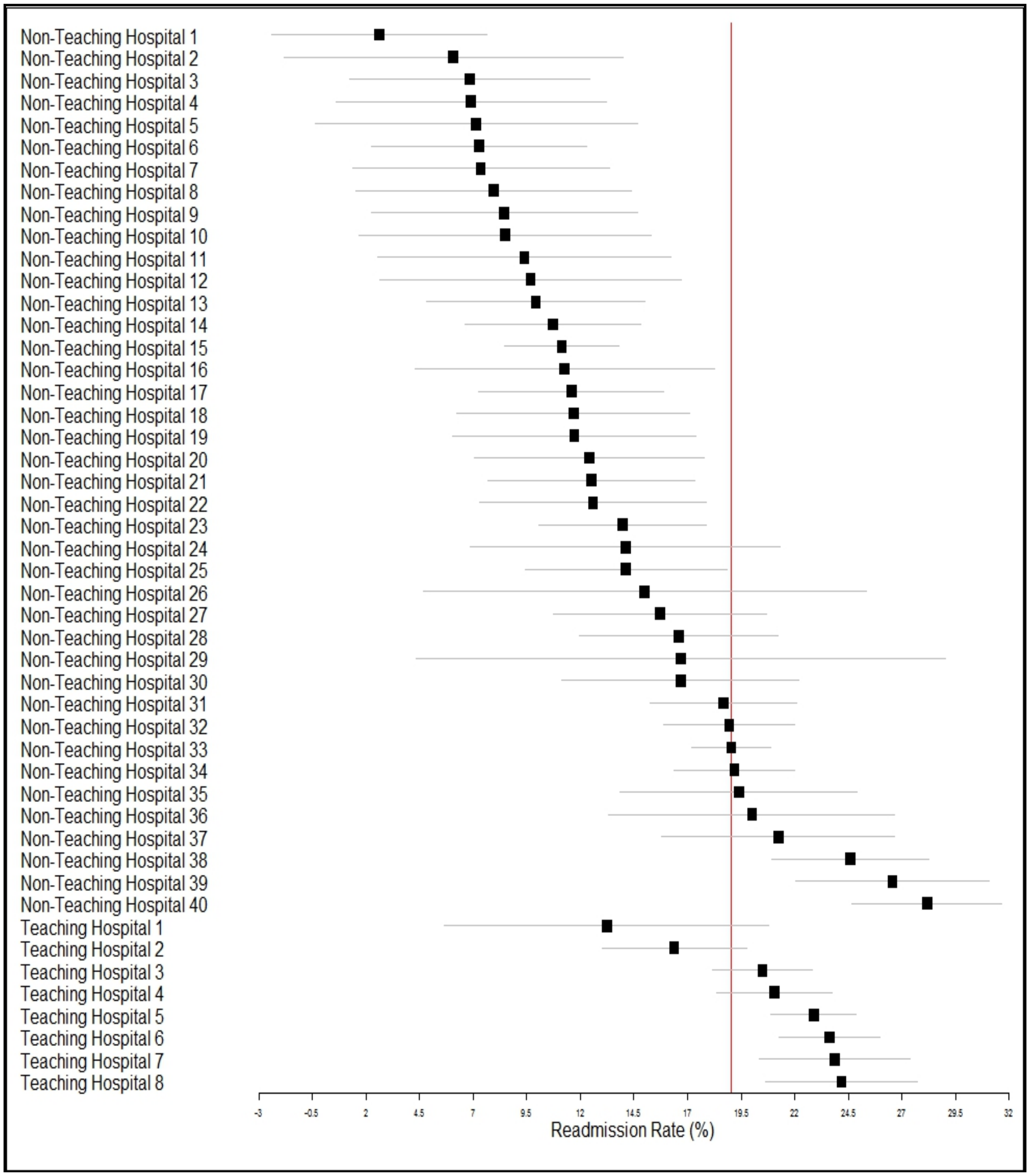
Note: All estimates are insignificant at alpha = 0.05 level.
N= 12,875, the number of Index AMI Hospitalizations

For each included variable in the Cox Proportional Hazards model, the null hypothesis is that each categorical variable does not affect the timing of readmission. Failure to reject the null hypothesis is illustrated by a 95% confidence interval containing the value of one. The alternative hypothesis is that there is an impact, either positive or negative, is represented by a 95% confidence interval either entirely above or below the value of one. Hazard ratios represent the ratio of readmission rates corresponding to the levels of the explanatory variables. The Cox Proportional Hazards model indicates that the timing of patient readmissions to the hospital are not influenced by the analyzed demographic factors or by hospital teaching status because the 95% confidence intervals for the calculated hazard ratios all contain the value of one. These findings support Dharmarajan et al. (2013) where no significant difference was found in the rate, or timing, of readmissions when analyzed by demographic characteristics.

While the timing of a readmission may not be correlated to socioeconomic factors or hospital teaching status, the logistic regression results indicate that socioeconomic factors and hospital teaching status do contribute to likelihood of readmission. The latter is the most relevant with regard to possible policy changes. For a given hospital deemed to have "excess" readmission which would result in a reimbursement penalty, as discussed in chapters I and II, the lower bound on the 95% confidence interval for the hospital readmission rate must exceed the national hospital readmission average (YNHHSC, 2014). Hospitals are penalized when their readmission rates for any diagnosis category (acute myocardial infarction, heart failure, pneumonia, chronic obstructive pulmonary disease, total knee arthroplasty, and total hip arthroplasty) exceed the national average rate. In the subsequent analysis, excess readmission rates are subject to the penalty structure provided by Yale New Haven Health Services (2014), for South Carolina hospitals with excess AMI readmissions.

Appendix E reports the summary data for the 48 South Carolina hospital's AMI admissions, the number of AMI readmissions, the proportion of AMI readmissions and the percentage of poor patients. Appendices E and F provide summary data used in the following forest plots and quintile analysis reported in this chapter. In this analysis, under current protocol, a hospital is considered to have an excess readmission rate if a hospital's lower bound for the 95% confidence interval for its AMI readmission rate is above the state-wide average. Here, the state-wide average is the total number of 30-day readmissions divided by the total number of index AMI admissions for the state (19.0%). The statewide average is a weighted average based on the number of AMI patients each hospital treats relative to the total number of AMI patients in the state. Using the weighted average for these comparisons is considered superior to a simple numeric average across all individual hospital rates because it takes into account differences in the number of AMI admissions in each of the 48 hospitals, which ranges from 33 to 1,476. Appendix F reports both methods of calculating the reference average readmission rates relative to the percentage of poor patients in each quintile. Under the proposed MEDPAC protocol, a hospital is considered to have an excess readmission rate if the hospital's lower bound for the 95% confidence interval for its AMI readmission rate is above its quintile average. The 95% confidence intervals are calculated using the standard calculation for a sample proportion.

Figure 5.1: Forest Plot of all Hospital Readmission Rates and 95% Confidence Intervals.



Note: Each horizontal line represents the readmission rate (black box) and 95% confidence interval of each hospital as indicated by the vertical axis. The vertical red line represents the weighted average state wide readmission rate =19.03%. Penalized hospitals are represented by hospitals whose entire 95% confidence interval is to the right of the vertical red line.

The average readmission rate for the analyzed South Carolina hospitals is 19.0% , and is denoted by the vertical red line in Figure 5.1. The horizontal axis for Figure 5.1 through Figure 5.6 is readmission rate, and the vertical axis represents hospitals by identification number. Among the 48 analyzed hospitals, 8 are teaching hospitals and 40 are non-teaching hospitals. The readmission rate for these 48 hospitals range from 2.6% to 28.2%. Applying the standard CMS approach (comparison to the state-wide readmission rate) reveals that 7 (14.6%) of the 48 hospitals have excess readmissions (i.e., the lower confidence interval bound for each of the hospitals exceeds the state-wide rate of 19.0%) and would incur reimbursement penalties under the current excess hospital readmission methodology. Recall, under the CMS methodology, the reference readmission rate is the nation-wide average rate. Given that only state-wide data is available, this study substitutes the state-wide readmission rate for the national reference rate. Another difference in this analysis is the readmission data for South Carolina's AMI population spans the years 2007-2011, whereas the CMS procedure calculates the nation-wide readmission rate on a 3 year moving average basis[3]. Of the 7 South Carolina hospitals that would be penalized under existing CMS methodology when the average state-wide rate is used as the reference, four are teaching hospitals (4 out of 8) and three (3 out of 40) are non-teaching hospitals. Thus, 50.0% of teaching hospitals have excess readmission rates compared to only 7.5% of non-teaching hospitals when the unadjusted state-wide average rate is used to determine excess readmission.

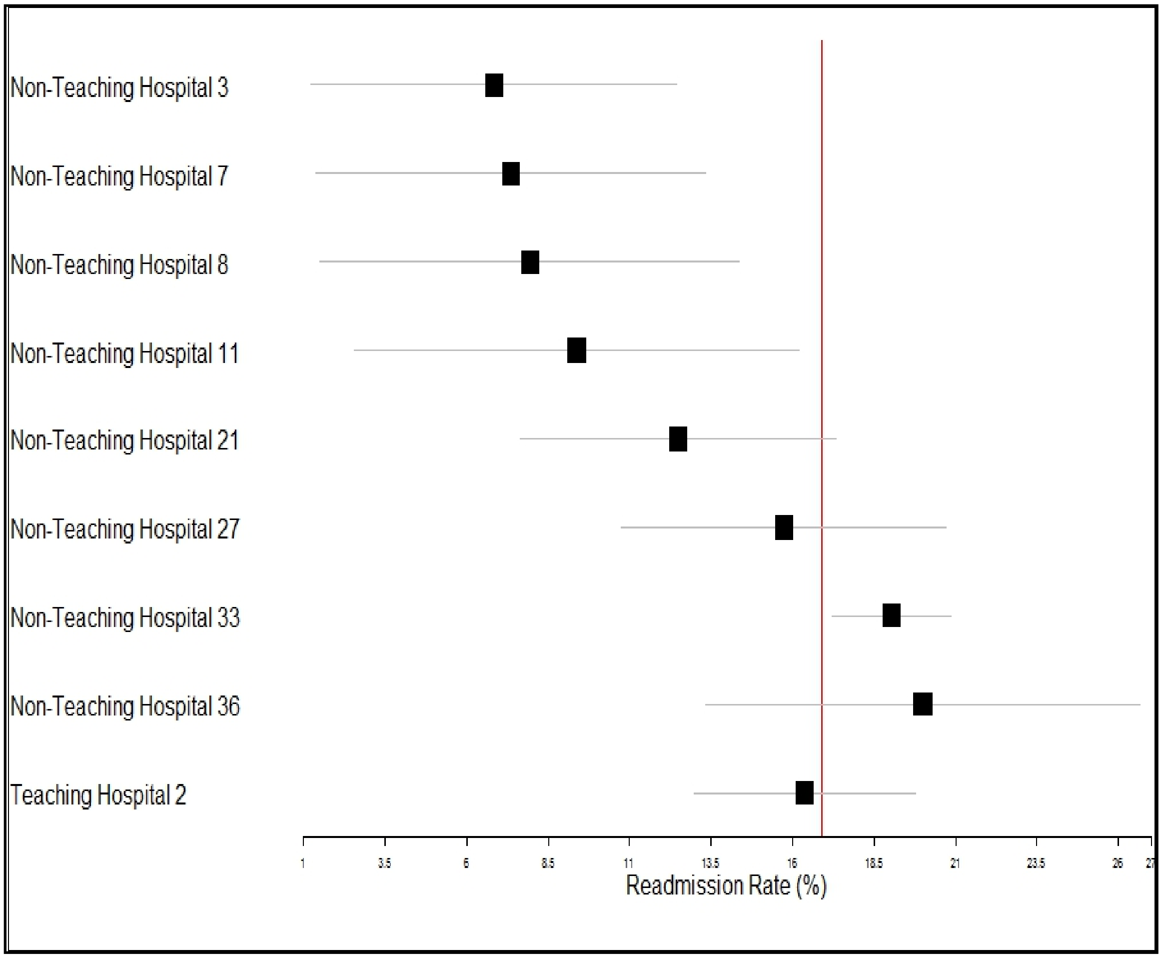
[3] The primary reason for using 5 years of data rather than 3 is because the data used in this study contains all payers rather than a true Medicare database. Moreover, the data base used here contains a sample of Medicare patients in South Carolina rather than all Medicare hospitalizations.

Current CMS protocol does not include any measure of socioeconomic status, a risk adjustment procedure, when estimating excess hospital readmission rates and subsequently assessing reimbursement penalties. Historically, a major reason for not including an adjustment for patient mix, is the belief that a socioeconomic patient adjustment will mask differences among hospitals and reduce hospital incentives to improve the quality of care for vulnerable populations (YNHHSC, 2014). While this may be a valid point, the issue is much larger than the quality of care provided to this "vulnerable" population. The population of poor patients arrives at various hospitals in an exogenously heterogeneous manner. Thus, the current method of calculating excess readmission penalties negatively impacts larger teaching hospitals to a greater degree due to inherent characteristics of their patients beyond their control.

Chapter II reviewed the Medicare Payment Advisory Committee (MEDPAC, 2013) report, which outlined an alternative method for adjusting readmission penalties to include the proportion of poor patients served by a hospital. The authors of this report found that the share of low-income patients is a strong predictor of hospital readmissions. Thus, in this study, the percentage of poor patients (i.e., indigent and Medicaid patients) at each hospital were stratified into quintiles (as reported in Table 4.3) to proxy for and isolate the relationship between the share of low income patients and hospital readmission rate.

An overall readmission rate for each of the five quintiles was calculated. Each hospital's average readmission rate and 95% confidence interval was calculated and compared to the weighted quintile average readmission rate the hospital belonged to, to determine if the hospital had an excess rate of readmissions relative to similar hospitals. The first quintile summarizes the AMI readmission values for hospitals having the lowest proportion of poor patients, and the fifth quintile summarizes the AMI readmission rates for hospitals with the highest proportion of low income patients.

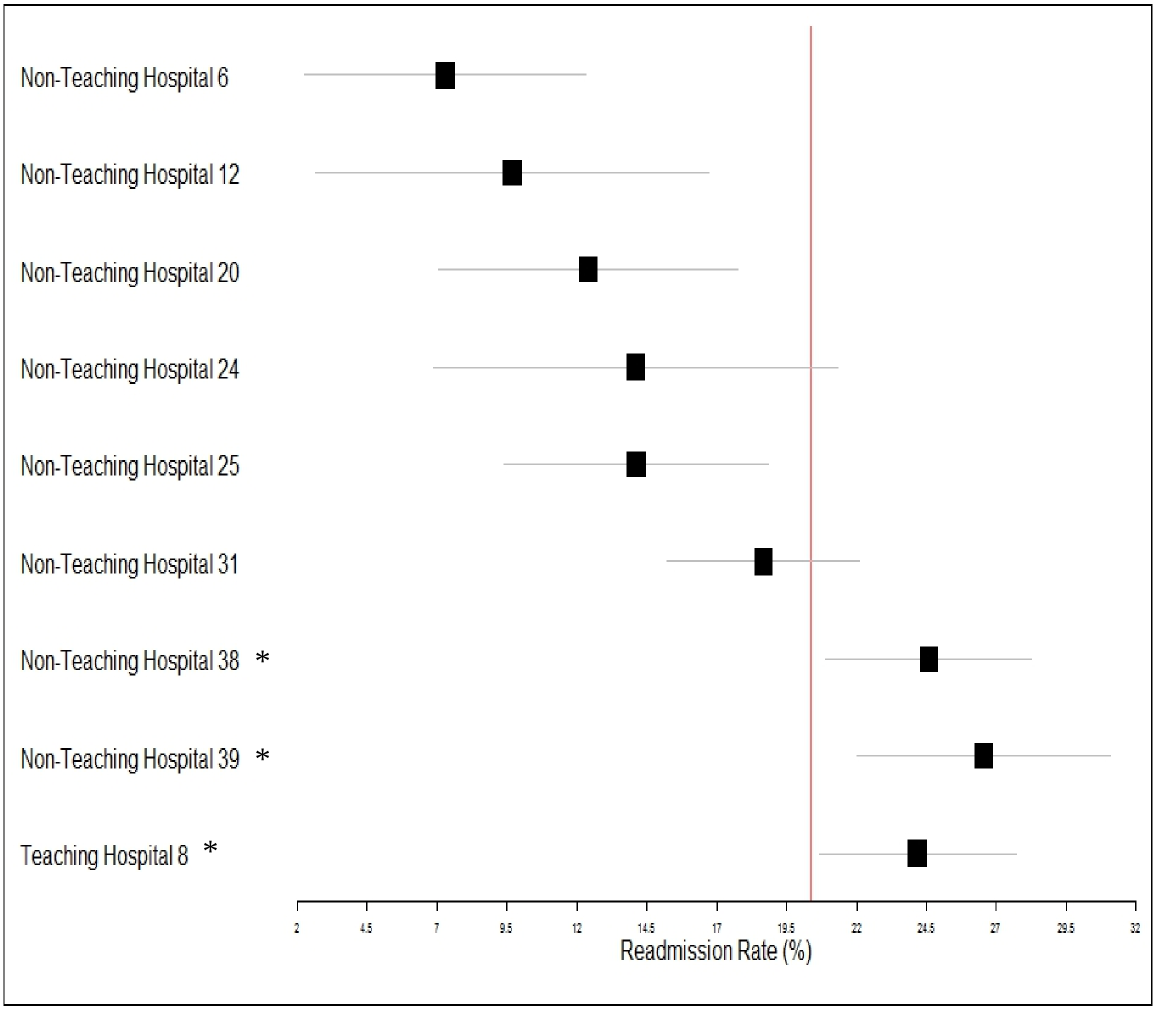
Figure 5.2: Forest Plot for Quintile 1 (Hospitals with the lowest proportion of poor patients) Hospital Readmission Rates and 95% Confidence Intervals



Note: Quintile 1 represents hospitals with the lowest proportion of poor patients (Indigent and Medicaid) in South Carolina. The proportion of low income patients in quintile 1 ranged from 4.74% to 7.52%. Each horizontal line represents the readmission rate (black box) and 95% confidence interval of each hospital as indicated by the vertical axis. The vertical red line represents the first quintile weighted average readmission rate of 16.89%. Penalized hospitals are represented by hospitals whose entire 95% confidence interval is to the right of the red line. *Denotes hospitals deemed to have excessive readmission rates based on the quintile approach.

Figure 5.2 uses a forest plot to report the confidence intervals for the 9 hospitals in the first quintile. The percentage of poor patients served by hospitals in the first quintile range from 4.74% to 7.52%. The 9 hospitals had an overall weighted average readmission rate of 16.89%, as indicated by the vertical red line. Of the 9 hospitals, only one (Non-Teaching Hospital 33) had a readmission rate where the lower bound of the 95% confidence interval was above the average quintile readmission rate of 16.89% deeming that hospital to have excess readmissions (i.e., the one hospitals with its confidence interval entirely to the right of the vertical red line). The one teaching hospital in this quintile did not have excess readmissions using the quintile criteria.

Figure 5.3: Forest Plot for Quintile 2 (hospitals with the second lowest proportion of poor patients) Hospital Readmission Rates and 95% Confidence Intervals

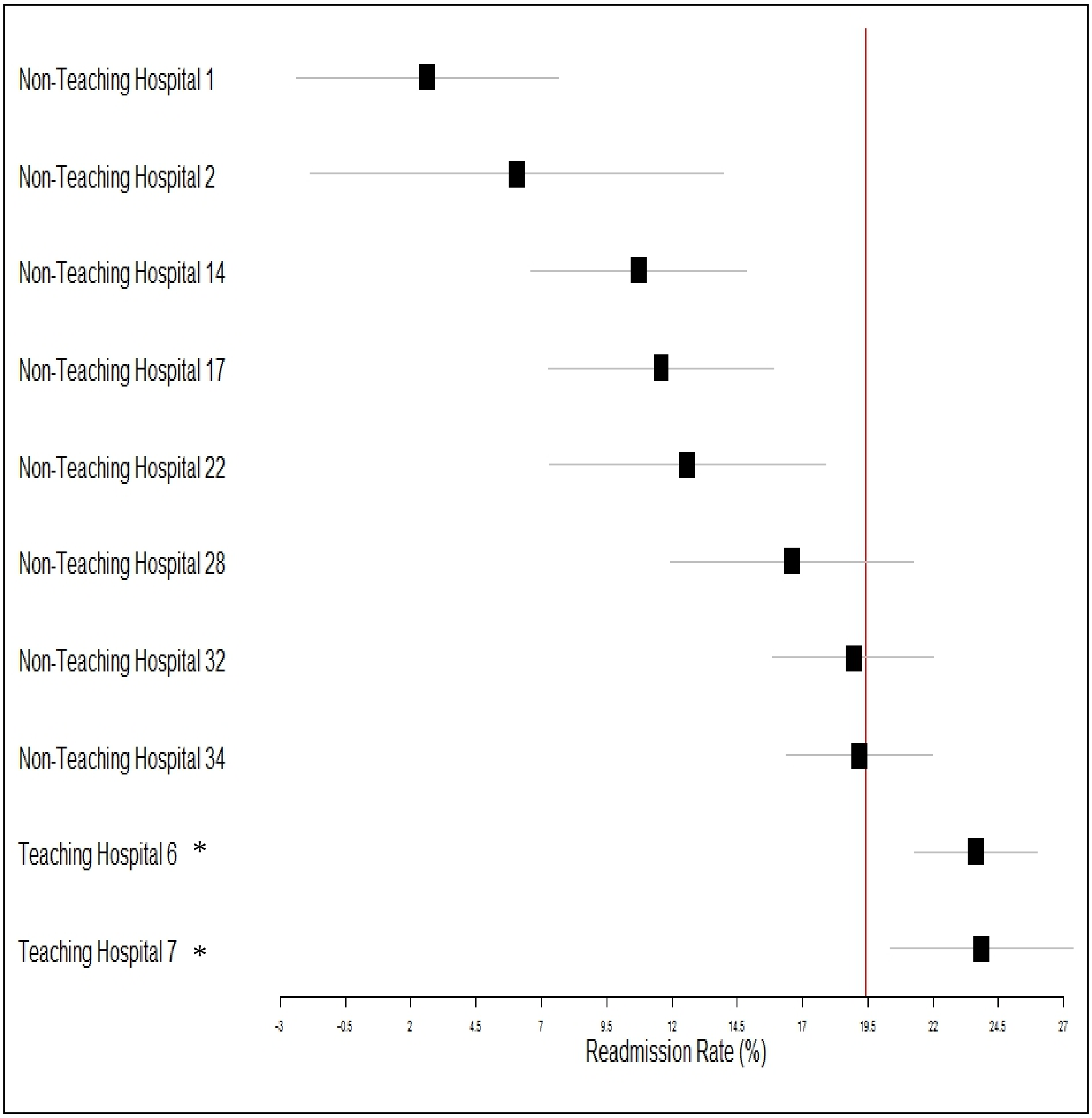


Note: Quintile 2 represents hospitals with the second lowest proportion of poor patients (Indigent and Medicaid) in South Carolina. The proportion of low income patients in the second quintile ranged from 7.69% to 9.49%. Each horizontal line represents the readmission rate (black box) and 95% confidence interval of each hospital as indicated by the vertical axis. The vertical red line represents the second quintile weighted average readmission rate of 20.37%. Penalized hospitals are represented by hospitals whose entire 95% confidence interval is to the right of the red line. *Denotes hospitals deemed to have excessive readmission rates based on the quintile approach.

The forest plot in Figure 5.3 displays readmission rates and confidence intervals for the second quintile that includes those hospitals with between 7.69% and 9.49% Medicaid or indigent patients. The second quintile also includes 9 hospitals and the overall weighted average readmission rate is 20.37%. Of the 9 hospitals, three (Non-Teaching Hospitals 38 and 39, and Teaching Hospital 8) have excess readmission rates relative to the quintile rate, including one teaching hospital. Unexpectedly, the second quintile has the highest readmission rate among the five quintiles despite the fact that this quintile has a relatively low proportion of Medicaid and indigent patients. This anomaly is likely a function of the state-wide data presented here rather than reflective of a nation-wide dataset. As the MEDPAC (2013) report to Congress showed, readmission rates are directly correlated to the proportion of poor patients with each group level readmission rate increasing as the proportion of poor patients increases. It is assumed that there will be a stronger positive correlation between readmission rates and the proportion of Medicaid and indigent patients as sample size increased from state-wide data to a nationally representative database. If this not the result, then additional research will be needed to explain this unexpected outcome.

The forest plot in Figure 5.4 displays readmission rates and confidence intervals for the third quintile that represents hospitals with a proportion of Medicaid and indigent patients ranging from 9.57% to 11.15%. The third quintile contains 10 hospitals with an average weighted readmission rate of 19.43%. Of the 10 hospitals in this quintile, two have excess readmission rates, both are teaching hospitals (Hospital 6 and Hospital 7.)

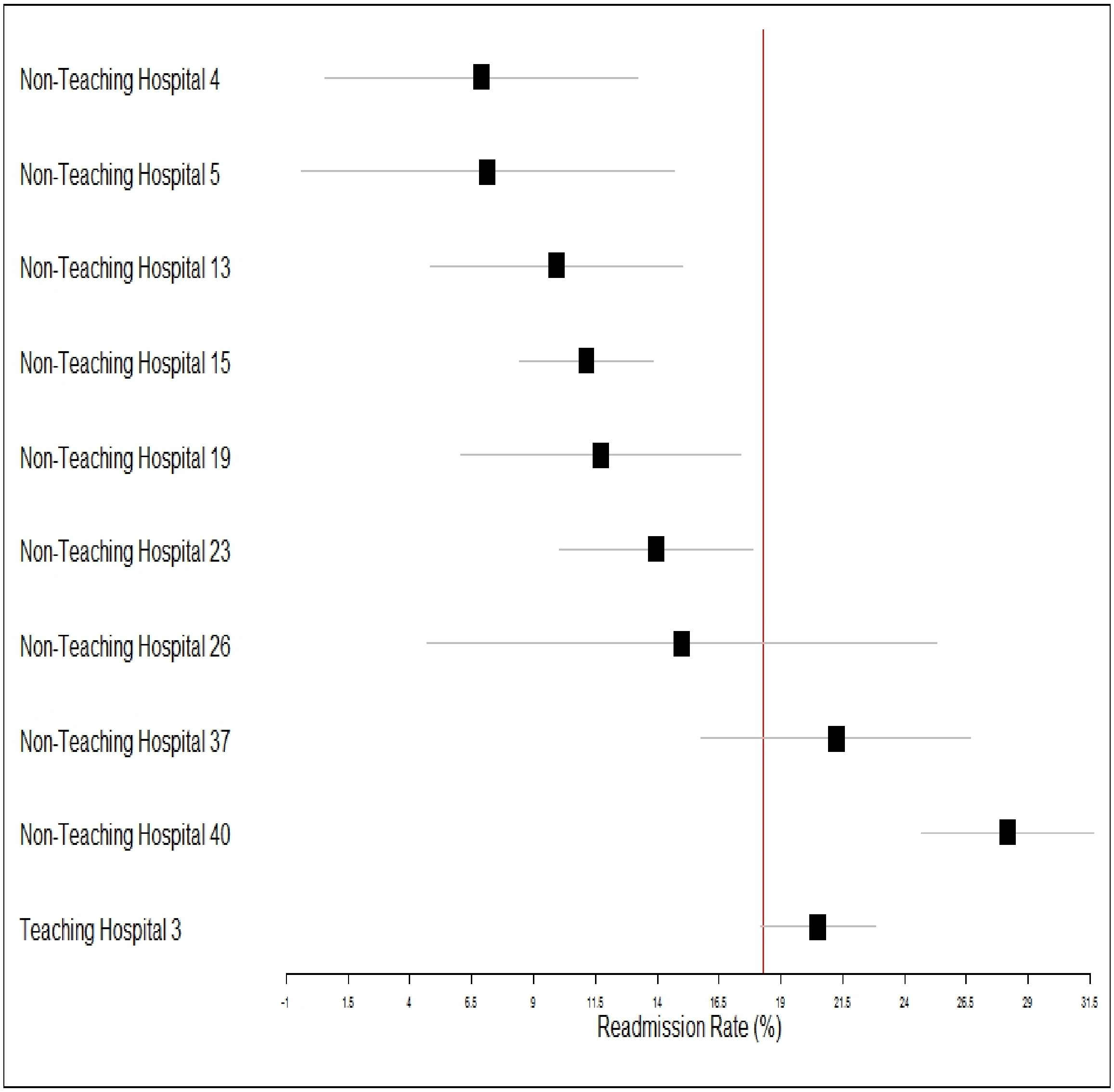
Figure 5.4: Forest Plot for Quintile 3 (hospitals with the third lowest proportion of poor patients) Hospital Readmission Rates and 95% Confidence Intervals



Note: Quintile 3 represents hospitals with the third lowest proportion of poor patients (Indigent and Medicaid) in South Carolina. The proportion of low income patients in the third quintile ranged from 9.57% to 11.15%. Each horizontal line represents the readmission rate (black box) and 95% confidence interval of each hospital as indicated by the vertical axis. The vertical red line represents the third quintile weighted average readmission rate of 19.43%. Penalized hospitals are represented by hospitals whose entire 95% confidence interval is to the right of the red line. *Denotes hospitals deemed to have excessive readmission rates based on the quintile approach.

The forest plot illustrated in Figure 5.5 displays readmission rates and confidence intervals for the fourth quintile that represents hospitals having a proportion of Medicaid and indigent patients between 11.31% to 15.64%. The fourth quintile includes 10 hospitals that have an average weighted readmission rate of 18.30%. Among the 10 hospitals, one (Non-Teaching Hospital 40) has an excess readmission rate relative to the quintile average rate.

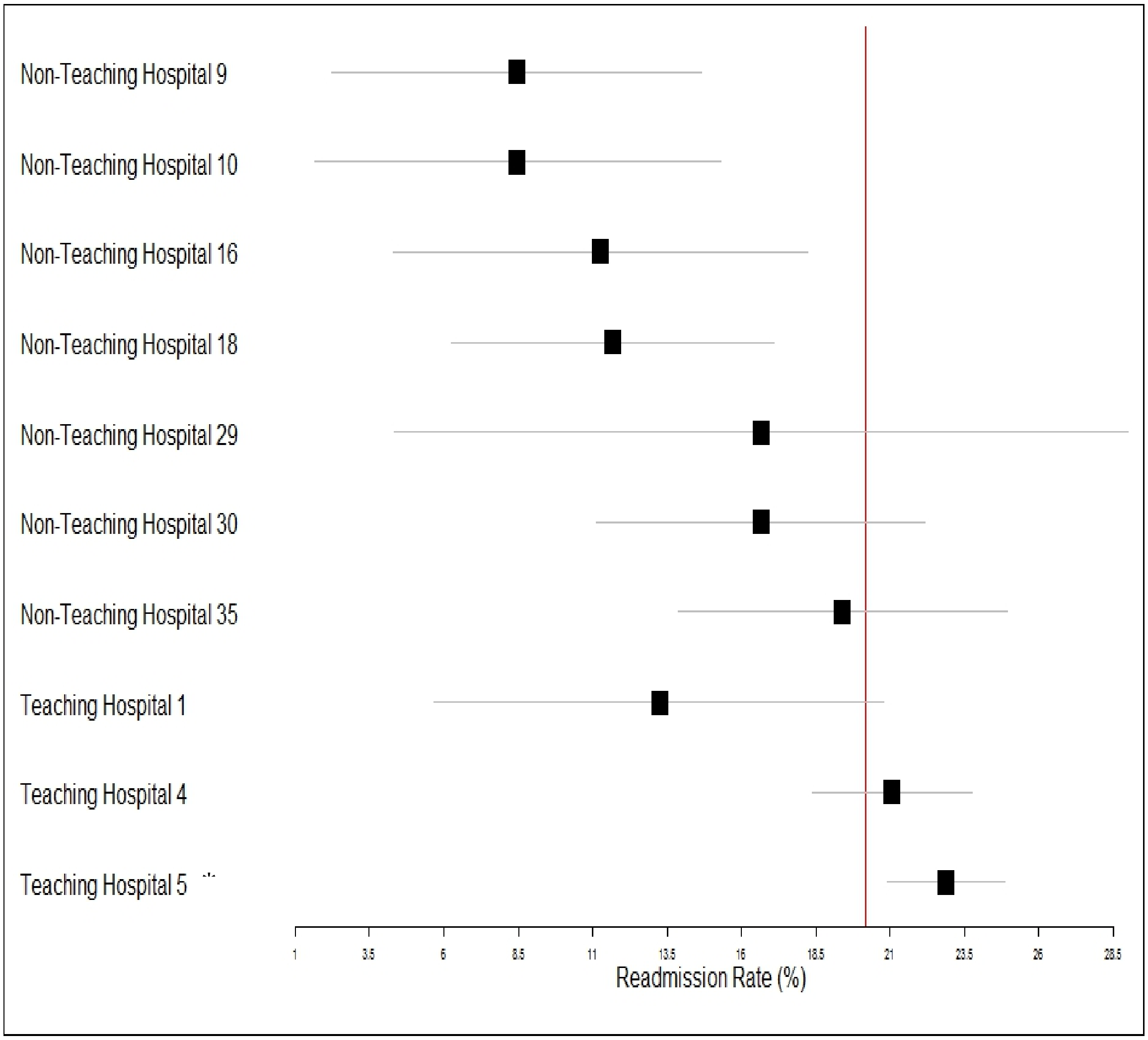
Figure 5.5: Forest Plot for Quintile 4 (hospitals with the second highest proportion of poor patients) Hospital Readmission Rates and 95% Confidence Intervals



Note: Quintile 4 represents hospitals with the second highest proportion of poor patients (Indigent and Medicaid) in South Carolina. The proportion of low income patients in the fourth quintile ranged from 11.31% to 15.64%. Each horizontal line represents the readmission rate (black box) and 95% confidence interval of each hospital as indicated by the vertical axis. The vertical red line represents the fourth quintile weighted average readmission rate of 18.3%. Penalized hospitals are represented by hospitals whose entire 95% confidence interval is to the right of the red line. *Denotes hospitals deemed to have excessive readmission rates based on the quintile approach.

Figure 5.6 displays the forest plot of readmission rates and confidence intervals for the fifth quintile that represents hospitals with the highest proportion of Medicaid and indigent patients. The proportion of poor patients at these 10 hospitals ranges from 15.68% to 21.55%. The overall weighted readmission rate for the 10 hospitals in the fifth quintile is 20.19%. Among the 10 hospitals, one (Teaching Hospital 5) has an excess readmission rate and this one hospital is a teaching hospital.

Figure 5.6: Forest Plot for Quintile 5 (hospitals with the highest proportion of poor patients) Hospital Readmission Rates and 95% Confidence Intervals



Note: Quintile 5 represents hospitals with the highest proportion of poor patients (Indigent and Medicaid) in South Carolina. The proportion of low income patients in the fifth quintile ranged from 15.68% to 21.55%. Each horizontal line represents the readmission rate (black box) and 95% confidence interval of each hospital as indicated by the vertical axis. The vertical red line represents the fifth quintile weighted average readmission rate of 20.19%. Penalized hospitals are represented by hospitals whose entire 95% confidence interval is to the right of the red line. *Denotes hospitals deemed to have excessive readmission rates based on the quintile approach.

The preceding descriptive analysis provides a procedure for determining when a hospital has an excess readmission rate that allows the administrative agency to control for exogenous patient mix characteristics that influence patient remittance. These patient characteristics are independent of overall hospital care quality but influence hospital readmission rates. Although this approach does not directly risk adjust for socioeconomic status, hospitals are grouped by the proportion of poor patients served thereby providing a means of addressing differences in patient mix among hospitals. Comparing the readmission rate of a hospital in each quintile group to their quintile average partially removes the impact of patient mix on readmission status while maintaining a standard of patient care.

Figure 5.1 through Figure 5.6 provide a visual means to identify hospitals that have excess readmission and therefore would be penalized (i.e., hospitals with the entire 95% confidence interval to the right of the vertical average quintile rate line) as well as hospitals that would not be penalized (i.e., hospitals with 95% confidence intervals that cross the vertical average line or are to the left of the vertical line). However, these graphics do not provide a clear measure of the degree to which each hospital will be penalized. Penalties for excess readmissions result in a percentage reduction in Medicare reimbursements. CMS currently uses a proprietary algorithm, which translates the degree to which a hospital's excess readmission rate is above the national rate into a downward payment adjustment. The maximum downward adjustment factor is 3%. In this analysis, excess readmissions penalties are calculated as the distance between a hospitals average readmission rate and the state-wide (or quintile based) average readmission rate. Using this methodology, excess readmission penalties are estimated for the current penalty structure (state-wide) and compared to the proposed penalty structure (quintile based). The estimated penalty calculation in this analysis is the difference between hospital readmission rate and comparative in-state quintile level average readmission rate. This procedure is not representative of the traditional Medicare reduction penalty used by CMS, which is a function of the overall average (not quintile average) rate. The crude penalty calculation used for this analysis is the average excess readmission rate in percentage terms for all hospitals having excess readmission in a given quintile. For example, if 3 hospitals in a quintile have excess readmission rates, and the distances between their readmission rates and the quintile reference rate are 1%, 2%, and 3%, respectively. The average readmission penalty for the three hospitals is 2%. In the following analysis the percent penalty reduction is assumed to be equal to the average excess readmission rate.

The estimated penalty amounts are presented in Table 5.5 for all hospitals, teaching hospitals, and non-teaching hospitals using both the state-wide average and quintile-level average comparisons. Using the state-wide comparison approach, a total of 7 hospitals were penalized at an average estimated rate of 5.81%. Four teaching hospitals had an excess readmission rate of 4.61%, and three non-teaching hospitals had an average excess readmission rate of 7.41%. In contrast, the quintile-level comparison revealed 8 hospitals would face penalty based on their average excess readmission rate of 4.69%. Furthermore, the quintile level comparison produced 4 teaching hospitals with an average penalty of 3.78%, based on an excess average readmission rate of 3.78%, and 4 non-teaching hospitals had an average penalty of 5.61%.

Table 5.5: Mean reimbursement penalty as a percentage decrease of full reimbursement under existing average approach versus quintile level approach

	Existing Penalty Calculation		Quintile Penalty Calculation		Percent Change in Penalty
	Estimated Penalty*	No. Hospitals Penalized	Estimated Penalty*	No. Hospitals Penalized	Using Quintile Approach
All Hospitals	5.81 ± 1.86	7	4.69 ± 2.40	8	-19.3
Teaching Hospitals	4.61 ± 0.55	4	3.78 ± 0.77	4	-18.0
Non-Teaching Hospitals	7.41 ± 1.79	3	5.61 ± 3.29	4	-24.3

*Estimated penalties are represented as mean ± standard deviation difference between hospital average and reference group average (state-wide or quintile)

The most important empirical result is the overall penalty is 19.3% less (4.69% versus 5.81%), with quintile averages than the state-wide average. It is hypothesized that this reduction in penalty is correlated to the populations of poor (indigent and Medicaid) which are now, to at least some degree, controlled for through the quintile-level analysis. While not directly adjusting for socioeconomic status, the quintile-level approach represents a method that indirectly controls for the percentage of poor patients who have been shown to disproportionally be readmitted.

Another finding likely a function of the South Carolina data and hence not representative of the nation as based on the literature, (Joynt and Jha 2013, Shimizu 2014, Muller 2013, Shahian 2012) is the estimated penalty reduction for non-teaching hospitals (24.3%) is greater than for teaching hospitals (18.0%). That is, relative to the national average approach, the quintile level approach provides greater penalty relief to non-teaching hospitals than teaching hospitals in South Carolina. Despite this unexpected outcome, these results are consistent with the hypothesis that grouping hospitals into income quintiles based on the proportion of poor patients they serve would marginally reduce the reimbursement penalty. It is important to note that these are aggregate measures and not direct comparisons of the two penalty estimates at the same hospital. That analysis is conducted later in this chapter.

The important finding is that non-teaching hospitals have larger penalties than the non-profit teaching hospitals that arguably cannot turn patients away. It is uncertain if this result is an anomaly of the South Carolina dataset. Further analysis incorporating national level data would be needed to resolve that issue. One possible explanation of this anomaly might be that teaching hospitals are better equipped to handle the sickest of the sick which could offset the effect of the difference in share of low income patients between non-profit teaching hospitals and for-profit non-teaching hospitals.

The results presented in Table 5.5 are based on the assumption that the average state-wide mean readmission rate and each quintile mean readmission rate are equal to the true but unknown respective population readmission rates. However, the loss of independence created by calculating each hospital's readmission rate and aggregating those data for the 48 hospitals' to determine the comparative statewide and quintile level readmission rates must be controlled for. The loss of independence here is that the weighted average state-wide readmission rate is comprised of each of the 48 hospital's data, to which the individual hospitals are compared for penalty determination. Thereby making the aggregate state-wide average dependent upon each hospital's readmission data. To address this issue, a series of 1,000 bootstrapped readmission rates were sampled with replacement for each of the 48 hospitals. Aggregating each resampled readmission rate for all 48 hospitals resulted in 1,000 state-wide readmission rates for comparison. The bootstrapping process allows for the analysis of how often each hospital is determined to have excess readmission rates as a proportion of the 1,000 tested samples. Recalling from the empirical analysis, a hospital is deemed to have excess readmissions if the lower bound of the 95% confidence interval is entirely above the state-wide rate, or quintile level rate. The bootstrapping process allows for analysis of the 48,000 bootstrapped hospital samples to be compared to 1,000 state-wide averages, as well as 5,000 quintile group averages (1,000 for each quintile) as a means of evaluating the empirical analysis. The computer code for the bootstrap analysis is provided in Appendix D.

Table 5.6 presents the bootstrapping results in a similar manor to Table 5.5. Similar trends emerge from the bootstrapped analysis. For all hospitals, the excess readmission penalty is less under the quintile approach than the state-wide average approach (5.83% versus 6.17%). However, the percentage reduction is only 5.51% less using the bootstrap approach versus the 19.3% reduction in the non bootstrap estimation. The discrepancy noted between the two empirical approaches is likely due to the impact of using aggregate hospital data to determine the state-wide average readmission rate, then comparing the individual hospital's readmission rate to that state-wide average. The bootstrap analysis also revealed similar reductions in the readmission penalty for both teaching and non-teaching hospitals. Non-profit teaching hospitals have a 7.66% reduction in penalty amount, and the percent reduction for the for non-teaching hospitals is 8.83%. The bootstrapped results confirm the readmission penalty decreases across all hospitals when the quintile average is used as the reference measure. However, these average results do not reveal the full difference in penalty amounts between the two methods for each individual hospital.

Table 5.6: Mean reimbursement penalty as a percentage decrease of full reimbursement under existing average approach versus quintile approach based on 1,000 bootstrapped samples.

	Existing Penalty Calculation		Quintile Penalty Calculation		Percent Change in Penalty Using Quintile Approach
	Estimated Penalty*	No. Hospitals Penalized **	Estimated Penalty*	No. Hospitals Penalized **	
All Hospitals	6.17 ± 2.43	18	5.83 ± 2.40	19	-5.51
Teaching Hospitals	4.83 ± 1.49	6	4.46 ± 1.40	7	-7.66
Non-Teaching Hospitals	7.93 ± 2.32	12	7.23 ± 3.02	12	-8.83

*Estimated penalties are represented as mean ± standard deviation difference between hospital average and reference group average (state-wide or quintile)

** If any of the 1,000 samples resulted in a penalty for a particular hospital

To further analyze the difference between the two methods, the difference in same hospital penalties were calculated. As before, the amount of penalty is proxied by the difference between a hospital's readmission rate and the state-wide (or quintile-level) comparison, only for hospitals deemed to have excess readmissions. Direct comparison of the difference in penalty value for the same hospital provides a more useful metric for assessing the difference in penalty structures. If a hospital was not penalized under the original method but is subsequently penalized using the quintile-level comparison, the difference is the entirety of the new penalty. Conversely, if a hospital is penalized using the state-wide comparison and is not penalized using the quintile-level comparison, the difference is the negative amount of the original penalty.

Table 5.7 Difference in Amount of Penalty For State-Wide and Quintile-Level Comparisons

	Same Hospital Penalty Difference*	
	Empirical Data	Bootstrapped Data
All Hospitals	-0.38	-0.69
Teaching Hospitals	-0.83	-1.12
Non-Teaching Hospitals	0.05	-0.22

*Amounts are represented as averages for respective groups, where Penalty difference = (Quintile-level penalty) - (State-Wide penalty)

Table 5.7 reports the difference in penalty amount between the state-wide and quintile-level comparisons. For each hospital, both methods of calculating excess readmissions penalties were performed, then the difference between the quintile level method and state-wide method was calculated. The resulting differences are presented in Table 5.7 where negative values indicate the quintile-level method resulted in lower penalties than the state-wide method, conceivably representing the differences in exogenous socioeconomic characteristics. This approach reduces noise created among hospitals with very large or very small penalties by analyzing both methods of estimating excess readmission penalties for the same hospital. Comparing the estimated penalties from the state-wide and quintile level methods is a useful metric to show differences at the same hospital. Similar trends are seen in both Table 5.6 and Table 5.7, where hospitals are penalized less under the quintile-level method relative to the state-wide method. Furthermore, a larger reduction is seen for teaching hospitals than non-teaching hospitals (1.12% versus 0.22%); a result empirically estimated and then confirmed through the bootstrapped analysis.

In conclusion, analyzing excess readmissions relative to other hospitals with similar patient mix lessens the estimation bias caused by heterogeneous patient mixes in the current method used to calculate excess readmissions. Calculating excess readmissions rates and penalties using a similar method to the one proposed by MEDPAC will not necessarily reduced the overall number of hospitals facing penalties. Instead it helps to focus the problem of readmissions back to the quality issues the HRRP is designed to address.

Although the absolute reduction in excess readmissions penalties is not large, the percent reductions reveal the importance of considering patient socioeconomic characteristics when calculating excess readmission penalties. These results do not directly imply that reductions in readmission rate penalties resulting from a MEDPAC type penalty structure will reduce cost shifting. However, an overall reduction in excess readmissions for all hospitals will reduce financial penalties, which arguably could reduce the incentive hospitals have to shift cost. Furthermore, these results highlight the importance of "family" in the medical care market, as well as the importance of the prestige maximizing "charitable" member of the family, which are the nonprofit teaching hospitals. The "family" for medical care stands to benefit from a reduction in excess readmission rate penalties when socioeconomic factors are included in the penalty calculation.

It is important to note that the estimated penalty reductions in this study are proxies for the true penalty algorithm used by CMS. Another important consideration is that while the percentage improvement may seem small, once multiplied by the multimillion dollar Medicare reimbursements, their magnitude will reveal significant improvements in revenue streams among nonprofit teaching hospitals and the medical care market as a whole.

Using an appropriate national data set including financial data tied to hospitalizations, the excess readmissions penalty associated with a poorer patient mix can more fairly be calculated. Comparing these penalties under the current method (national comparison) and the new method (quintile/decile comparison) might reveal a reduction in the amount of penalty paid when compared to a cohort of hospitals with similar patient mix. The reduction in penalty could thereby reduce the potential need to shift cost to private insurers.

CHAPTER VI

CONCLUSIONS AND DISCUSSION

I. Introduction

Numerous studies have found that lower socioeconomic status contributes to the likelihood of readmission due to patients having less access to care, non-compliance to physician orders, and lower nutritional status, among many other reasons (Mueller et al. 2013, and Shahian et al. 2012, Philbin et al 2001, Shimizu et al. 2014). Joynt, Jha (2013) suggest that these differences are due in large part to patient socioeconomic factors and the greater proportion of medically complex cases larger teaching hospitals encounter relative to smaller non-teaching hospitals. Joynt and Jha also found that the level of Medicare reimbursement penalties is correlated with socioeconomic status. This prior research support the hypothesis that socioeconomic status tends to be negatively correlated with increased medical complexity. Moreover, low income patients tend to be admitted and readmitted to nonprofit teaching and safety net hospitals in a higher proportion of all admissions relative to other hospital types (Philbin et al., 2001).

This evidence, coupled with unique differences in optimization decisions between for-profit and nonprofit hospitals, sets the foundation to study excess readmissions penalties among two hospital types. For-profit hospitals can be expected to maximize profits as a function of increasing patient quantities. Nonprofit hospitals, however, are hypothesized to optimize prestige through maximizing revenues constrained by covering costs under a fixed operating margin subject to a unique mix of patients (Hirth, 1997; Horwtiz 2015; Rosenman et al., 2000). The incorporation of a nonprofit hospital's exogenously determined patient mix into optimization decisions requires these hospitals to offset potential losses from uncompensated care provided to poor and indigent patients by shifting costs to privately insured patients (Hadley and Feder, 1986; Dranove, 1988). A reinterpretation of Becker's 1974 essay *"A Theory of Social Interactions"* further supports the role of nonprofit hospitals in the market for medical care by positing that they can be viewed as acting as "charitable" family members. Nonprofit hospitals as "charitable" family members seek to maximize prestige through redistributing increased revenue from the privately insured to cover the cost of uncompensated care to poor and uninsured patients.

The unique nature of medical care markets, differences in hospital type and optimization decisions, and the knowledge that poor patients are readmitted in higher proportions to nonprofit teaching hospitals, prompted a review of the Hospital Readmission Reduction Program (HRRP). The current method of assessing excess readmissions penalties used by The Centers for Medicare and Medicaid Services (CMS) does not account for differences in patient mix. Evidence provided here supports the notion that socioeconomic factors and unique patient mix among the distribution of for-profit and nonprofit hospitals does impact readmission rates and resulting excess readmissions penalties.

The objectives of this research were to demonstrate the differences among hospital readmission rates and resulting penalties by hospital type and socioeconomic factors to demonstrate how the current Hospital Readmission Reduction program disproportionately penalizes nonprofit teaching hospitals for excess readmissions as a result of their exogenous patient mix.

II. Conclusions

To satisfy the research objective, a longitudinal data set of South Carolina inpatient hospital visits from January 1, 2007 through December 31, 2011 was used to document differences between for-profit hospitals and nonprofit teaching hospitals. The data were used to demonstrate the differences between the current method of calculating excess readmission rates and the new method proposed by the Medicare Payment Advisory Commission (MEDPAC, 2013) that groups hospitals based on the proportion of poor patients they serve.

Differences in patient mix between South Carolina for-profit and nonprofit teaching hospitals proxied by the percentage of Medicaid and indigent patients cared for by each hospital type were documented in Chapter IV. Non-profits were shown to have a greater percentage of indigent and Medicaid patients. This finding supports the growing body of literature that argues the unique mix of patients between hospital types requires different optimization decisions between for-profit and nonprofit hospitals. Moreover, comparing excess readmission penalties under the current program (CMS, HRRP) and the method proposed by MEDPAC suggests that incorporating patient mix into the excess readmission penalty will reduce readmission penalties and increase hospital revenue. Moreover, a reduction in excess readmission penalties would theoretically reduce the incentive to shift costs from those unable to pay to patients with the ability to pay. A secondary benefit of the proposed excess readmission penalty calculation is that it will more fairly assess the quality of hospital care.

As reported in Chapter V, both empirically and through the bootstrap simulations, adjusting a hospital's readmission rate to control for the proportion of poor patients reduces the level of excess readmission penalty. Furthermore, the socioeconomic adjustment benefits nonprofit teaching hospitals to a greater degree. The same hospital penalty reduction was 1.12% for nonprofit teaching hospitals and 0.22% for for profit non-teaching hospitals in the bootstrap analysis. The resulting difference between nonprofit and for-profit penalties provide support to the hypothesis that nonprofit hospitals serve as "charitable" members of the healthcare family by caring for the poorest members of society who are often the sickest.

III. Discussion

While these results are limited by a lack of more detailed data on patient characteristics, they provide support that socioeconomic status is an integral aspect of determining excess hospital readmissions. The Centers for Medicare and Medicaid Services (CMS), and the Yale New Haven Health Services Corporation (YNHHSC) make strong cases for not including socioeconomic status as a risk-adjustment factor when determining readmissions rates. These groups argue it is inappropriate to adjust for patient characteristics because all patients deserve the same quality of care regardless of socioeconomic status. While it is necessary and important to maintain quality standards in the medical care market, arguably, it is equally as important to note the differences in patient characteristics and patient mix between hospital types impact the excess readmission rate.

Current literature provides support for these findings, and the importance of modifying the excess readmission penalty to control for hospital patient mix. Barnett et al. (2015) used Health and Retirement Study surveys with linked Medicare claims from 2009 to 2012 and identified 29 patient characteristics outside of the standard risk adjustments used by Medicare to assess the extent to which these additional patient variables impact readmission rates. Of the 29 characteristics identified, 22 predicted readmission (Barnett 2015). Thus, there is a growing body of research that suggests patient specific factors contribute to the likelihood of readmission that are not currently incorporated into excess readmission calculations by CMS. Barnett et al. conclude

> *"Hospitals with high readmission rates may be penalized to a large extent based on the patients they serve (page E1)."*

The results of Barnett et al. suggest that hospital readmission is less likely to be explained by the quality of care provided to a patient, and more likely to be explained by the attributes of the patient. Fundamentals of medical care and the structure of the United States Healthcare system does not allow for most hospitals to control the patient populations they serve. Yet hospitals continue to be penalized for readmissions exogenous factors largely outside their control.

Recently, Zuckerman et al. addressed the issue of maintaining quality care in the presence of excess readmissions penalties (2016). They discuss the claim that some hospitals may circumvent possible readmission penalties by placing patients who return to the hospital within 30-days of a previous admission in "observational units" rather than readmitting the patient. The claim posits that some hospitals may use administrative and coding techniques to avoid penalties of having the patient readmitted. They analyzed 3,387 hospitals between 2007 and 2015 and found that changes in observational-unit stays did not account for decreases in readmissions (Zuckerman et al., 2016). This finding suggests that even though hospitals may attempt to to inappropriately circumvent penalties, such actions have not been successful at the individual hospital level.

Sheingold et al. (2016) address the issue of differences in readmissions penalties between nonprofit safety-net hospitals and other hospitals. They found that patient socioeconomic factors partly explain readmission rate differences, and safety-net hospitals have slightly higher readmission rates than other hospital types. The authors further conclude that their findings, among others currently in the literature, support the need for consideration of policy alternatives for excess readmission rate and penalty calculations (Sheingold et al., 2016).

The debate and discussion of policy changes to the Hospital Readmission Reduction program is continuously evolving. The current findings of Barnett et al., Zuckerman et al., and Sheingold et al., provide evidence and support that excess readmission penalty determination needs to incorporate patient level factors and hospital type considerations. The importance of these findings may result in policies that more accurately identify underperforming hospitals after controlling for patient mix. Furthermore, the resulting policy changes stand to improve the entire healthcare "family" by incorporating measures that highlight the need for the "charitable" nonprofit hospital in conjunction with for-profit hospitals to best treat populations in need of medical care.

IV. Study Limitations

The Hospital Readmission Reduction Program (HRRP) is a program directly attributed to the Medicare population. However, the data used contain a sample of South Carolina inpatient hospitalizations reported for patients of all ages, not just Medicare patients. While the data used contained some Medicare patients, it does not contain all inpatient hospitalizations for Medicare patients in the state. Therefore, the entire data set of all adult hospital claims was used because selecting only the Medicare population would have resulted in an insufficiently small dataset given the HRRP inclusion/exclusion criteria. Additionally, the collected dataset only included patients with index admissions for acute heart attacks (AMI), heart failure and pneumonia. Therefore, determination of the proportion of poor patients at each hospital and the resulting quintiles used for analysis is incomplete. To more accurately conduct this study all hospital admissions for any patient in the state during the study period are needed.

Furthermore, HRRP analyzes excess readmission rates using a rolling three-year average. Due to insufficient data to satisfy the requirements of The Centers for Medicare and Medicaid guidelines for calculating readmissions, a 5 year data series was used. Another limitation is the lack of risk adjusting, due to inadequate risk adjustment variables. A statewide database provides a unique and interesting perspective for conducting a study of excess readmissions calculations. However, a nationally representative, risk adjusted database of Medicare patients would best be able to determine the impact of proposed policy changes. The study is also limited due to the small sample size of teaching and non-teaching hospitals. Comparing 8 teaching hospitals to 40 non-teaching hospitals makes the results less robust than a national study. A comprehensive dataset that aggregated all United States teaching and non-teaching hospitals would provide the best data for this analysis.

Additional limitations include the inability to quantify the degree of nonprofit hospital prestige maximization. The notion of prestige maximization is discussed in the literature, but consensus on how to best quantify the theoretically ambiguous concept of prestige has never been reached. With appropriate data, profit maximization among for-profit hospitals could be determined. Further research is required to understand the interactions and optimization of nonprofit prestige maximizing hospitals and profit maximizing hospitals within the medical care "family".

The results presented here, in conjunction with current and future research provide some evidence for the need to improve the calculation of the excess readmission rate and penalty determinations through policy changes that incorporate patient level factors and hospital type. Changes to the Hospital Readmission Reduction Program as a result of this continued research stands to more fairly penalize hospitals while maintaining high quality standards of care.

APPENDICES

Appendix A

R Code for Variable Creation

```
#Index
AMImr<-read.csv("AMImr.csv",sep=",", header=TRUE)
AMImr$ADMD=as.Date(AMImr$ADMD,"%m/%d/%Y" )
AMImr$DISD=as.Date(AMImr$DISD,"%m/%d/%Y" )
AMISORT<-AMImr[order(AMImr$ID, AMImr$ADMD, AMImr$ADHOUR),]
N = nrow(AMISORT)
#AMISORT$RA = rep(NA, N)
AMISORT$Index = rep(NA, N)
#AMISORT$Transfer= rep(NA, N)
for(i in 2:N){
  if(AMISORT$AMI[i]==1 ){
    AMISORT$Index[i] = 1
  }
  else if (AMISORT$ID[i] == AMISORT$ID[i-1]  &&
AMISORT$ADMD[i]==AMISORT$ADMD[i-1] ){
    AMISORT$Index[i] = 0
 }
  else {
    AMISORT$Index[i] = 0
  }
}
write.csv(AMISORT, file="AMImrI.csv")


#Transfer
AMImrI<-read.csv("AMImrI.csv",sep=",", header=TRUE)
AMImrI$ADMD=as.Date(AMImrI$ADMD,"%m/%d/%Y" )
AMImrI$DISD=as.Date(AMImrI$DISD,"%m/%d/%Y" )
AMISORT<-AMImrI[order(AMImrI$ID, AMImrI$ADMD, AMImrI$ADHOUR),]
N = nrow(AMISORT)
#AMISORT$RA = rep(NA, N)
#AMISORT$Index = rep(NA, N)
AMISORT$Transfer= rep(NA, N)
for(i in 3:N){
  if(AMISORT$ID[i] == AMISORT$ID[i-1]  && AMISORT$ADMD[i] -
AMISORT$DISD[i-1]<=1 && AMISORT$Index[i-1]==1 && AMISORT$HID[i]
!=AMISORT$HID[i-1]){
    AMISORT$Transfer[i] = 1
```

```
  }
  else if (AMISORT$ID[i] == AMISORT$ID[i-1]  && AMISORT$ADMD[i] -
AMISORT$DISD[i-2]<=1 && AMISORT$Index[i-2]==1 && AMISORT$HID[i]
!=AMISORT$HID[i-1]){
    AMISORT$Transfer[i] = 1
  }
  else {
    AMISORT$Transfer[i] = 0
  }
}
write.csv(AMISORT, file="AMImrIT.csv", row.names=FALSE)



#RAi- Index readmission
AMImrIT<-read.csv("AMImrIT.csv",sep=",", header=TRUE)
AMImrIT$ADMD=as.Date(AMImrIT$ADMD,"%m/%d/%Y" )
AMImrIT$DISD=as.Date(AMImrIT$DISD,"%m/%d/%Y" )
AMISORT<-AMImrIT[order(AMImrIT$ID, AMImrIT$ADMD, AMImrIT$ADHOUR),]
N = nrow(AMISORT)
AMISORT$RAi = rep(NA, N)
#AMISORT$RAr = rep(NA, N)
#AMISORT$Index = rep(NA, N)
#AMISORT$Transfer= rep(NA, N)
for(i in 3:N){
  if(AMISORT$ID[i] == AMISORT$ID[i-1]  && AMISORT$AMI[i-1]==1 &&
AMISORT$Transfer[i]!=1){
    AMISORT$RAi[i-1] = 1
  }
  else if(AMISORT$ID[i] == AMISORT$ID[i-2]  && AMISORT$AMI[i-2]==1 ){
    AMISORT$RAi[i-2] = 1
  }
  else {
    AMISORT$RAi[i] = 0
  }
}
write.csv(AMISORT, file="AMImrITRi.csv", row.names=FALSE)

#RAi30
AMImrTIRir<-read.csv("AMImrTIRir.csv",sep=",", header=TRUE)
AMImrTIRir$ADMD=as.Date(AMImrTIRir$ADMD,"%m/%d/%Y" )
AMImrTIRir$DISD=as.Date(AMImrTIRir$DISD,"%m/%d/%Y" )
AMISORT<-AMImrTIRir[order(AMImrTIRir$ID, AMImrTIRir$ADMD,
AMImrTIRir$ADHOUR),]
```

```
N = nrow(AMISORT)
AMISORT$RAi30 = rep(NA, N)
#AMISORT$RAr = rep(NA, N)
#AMISORT$Index = rep(NA, N)
#AMISORT$Transfer= rep(NA, N)
for(i in 3:N){
  if(AMISORT$ADMD[i] - AMISORT$DISD[i-1]<= 30 && AMISORT$ID[i] ==
AMISORT$ID[i-1] &&  AMISORT$Index[i-1]==1 && AMISORT$Transfer[i]!=1){
    AMISORT$RAi30[i-1] = 1
  }
  else if(AMISORT$ADMD[i]-AMISORT$DISD[i-2]<=30 && AMISORT$ID[i] ==
AMISORT$ID[i-2]  && AMISORT$Index[i-2]==1 && AMISORT$RAi[i-1]!= 1){
    AMISORT$RAi30[i-2] = 1
  }
  else {
    AMISORT$RAi30[i] = NA
  }
}
write.csv(AMISORT, file="AMImrITRi30.csv", row.names=FALSE)
#RAi30t
AMImrTIRir3030<-read.csv("AMImrTIRir3030.csv",sep=",", header=TRUE)
AMImrTIRir3030$ADMD=as.Date(AMImrTIRir3030$ADMD,"%m/%d/%Y" )
AMImrTIRir3030$DISD=as.Date(AMImrTIRir3030$DISD,"%m/%d/%Y" )
AMISORT<-AMImrTIRir3030[order(AMImrTIRir3030$ID, AMImrTIRir3030$ADMD,
AMImrTIRir3030$ADHOUR),]
N = nrow(AMISORT)
AMISORT$RAi30t = rep(NA, N)
#AMISORT$RAr = rep(NA, N)
#AMISORT$Index = rep(NA, N)
#AMISORT$Transfer= rep(NA, N)
for(i in 3:N){
  if(AMISORT$ADMD[i] - AMISORT$DISD[i-1]<= 30 && AMISORT$ID[i] ==
AMISORT$ID[i-1] &&  AMISORT$Index[i-1]==1 && AMISORT$Transfer[i]!=1){
    AMISORT$RAi30t[i-1] = (AMISORT$ADMD[i] - AMISORT$DISD[i-1])
  }
  else if(AMISORT$ADMD[i]-AMISORT$DISD[i-2]<=30 && AMISORT$ID[i] ==
AMISORT$ID[i-2]  && AMISORT$Index[i-2]==1 && AMISORT$RAi[i-1]!= 1){
    AMISORT$RAi30t[i-2] = (AMISORT$ADMD[i] - AMISORT$DISD[i-2])
  }
  else {
    AMISORT$RAi30t[i] = NA
  }
}
write.csv(AMISORT, file="AMImrITRi3030t.csv", row.names=FALSE)
```

Appendix B

R-Code for Hospital Exclusion

```
AMI<-read.csv("AMImrITRi3030t.csv",sep=",", header=TRUE)
AMI$ADMD=as.Date(AMI$ADMD,"%m/%d/%Y")
AMI$DISD=as.Date(AMI$DISD,"%m/%d/%Y")
AMIsort<-AMI[order(AMI$ID, AMI$DISD),]
AMI07<-AMIsort[which(AMIsort$DISD<'2008-01-01'),]
AMI08<-AMIsort[which(AMIsort$DISD>'2007-12-31' & AMIsort$DISD<'2009-01-
01'),]
AMI09<-AMIsort[which(AMIsort$DISD>'2008-12-31' & AMIsort$DISD<'2010-01-
01'),]
AMI10<-AMIsort[which(AMIsort$DISD>'2009-12-31' & AMIsort$DISD<'2011-01-
01'),]
AMI11<-AMIsort[which(AMIsort$DISD>='2011-01-01'),]

table(AMI07$Index, AMI07$HID)
AMI$AMI07q<-0
AMI$AMI07q[which(AMI$HID==50)]=1
AMI$AMI07q[which(AMI$HID==105)]=1
AMI$AMI07q[which(AMI$HID==155)]=1
AMI$AMI07q[which(AMI$HID==220)]=1
AMI$AMI07q[which(AMI$HID==280)]=1
AMI$AMI07q[which(AMI$HID==310)]=1
AMI$AMI07q[which(AMI$HID==340)]=1
AMI$AMI07q[which(AMI$HID==347)]=1
AMI$AMI07q[which(AMI$HID==390)]=1
AMI$AMI07q[which(AMI$HID==420)]=1
AMI$AMI07q[which(AMI$HID==430)]=1
AMI$AMI07q[which(AMI$HID==450)]=1
AMI$AMI07q[which(AMI$HID==460)]=1
AMI$AMI07q[which(AMI$HID==490)]=1
AMI$AMI07q[which(AMI$HID==540)]=1
AMI$AMI07q[which(AMI$HID==565)]=1
AMI$AMI07q[which(AMI$HID==570)]=1
AMI$AMI07q[which(AMI$HID==575)]=1
AMI$AMI07q[which(AMI$HID==580)]=1
AMI$AMI07q[which(AMI$HID==590)]=1
AMI$AMI07q[which(AMI$HID==610)]=1
AMI$AMI07q[which(AMI$HID==630)]=1
AMI$AMI07q[which(AMI$HID==640)]=1
AMI$AMI07q[which(AMI$HID==645)]=1
AMI$AMI07q[which(AMI$HID==650)]=1
```

```
table(AMI08$Index, AMI08$HID)
AMI$AMI08q<-0
AMI$AMI08q[which(AMI$HID==50)]=1
AMI$AMI08q[which(AMI$HID==105)]=1
AMI$AMI08q[which(AMI$HID==155)]=1
AMI$AMI08q[which(AMI$HID==220)]=1
AMI$AMI08q[which(AMI$HID==280)]=1
AMI$AMI08q[which(AMI$HID==310)]=1
AMI$AMI08q[which(AMI$HID==340)]=1
AMI$AMI08q[which(AMI$HID==347)]=1
AMI$AMI08q[which(AMI$HID==390)]=1
AMI$AMI08q[which(AMI$HID==420)]=1
AMI$AMI08q[which(AMI$HID==430)]=1
AMI$AMI08q[which(AMI$HID==450)]=1
AMI$AMI08q[which(AMI$HID==460)]=1
AMI$AMI08q[which(AMI$HID==490)]=1
AMI$AMI08q[which(AMI$HID==540)]=1
AMI$AMI08q[which(AMI$HID==565)]=1
AMI$AMI08q[which(AMI$HID==570)]=1
AMI$AMI08q[which(AMI$HID==575)]=1
AMI$AMI08q[which(AMI$HID==580)]=1
AMI$AMI08q[which(AMI$HID==590)]=1
AMI$AMI08q[which(AMI$HID==610)]=1
AMI$AMI08q[which(AMI$HID==630)]=1
AMI$AMI08q[which(AMI$HID==640)]=1
AMI$AMI08q[which(AMI$HID==645)]=1
AMI$AMI08q[which(AMI$HID==650)]=1

table(AMI09$Index, AMI09$HID)
AMI$AMI09q<-0
AMI$AMI09q[which(AMI$HID==50)]=1
AMI$AMI09q[which(AMI$HID==105)]=1
AMI$AMI09q[which(AMI$HID==120)]=1
AMI$AMI09q[which(AMI$HID==155)]=1
AMI$AMI09q[which(AMI$HID==220)]=1
AMI$AMI09q[which(AMI$HID==280)]=1
AMI$AMI09q[which(AMI$HID==340)]=1
AMI$AMI09q[which(AMI$HID==345)]=1
AMI$AMI09q[which(AMI$HID==347)]=1
AMI$AMI09q[which(AMI$HID==420)]=1
AMI$AMI09q[which(AMI$HID==430)]=1
AMI$AMI09q[which(AMI$HID==450)]=1
AMI$AMI09q[which(AMI$HID==460)]=1
```

```
AMI$AMI09q[which(AMI$HID==490)]=1
AMI$AMI09q[which(AMI$HID==540)]=1
AMI$AMI09q[which(AMI$HID==565)]=1
AMI$AMI09q[which(AMI$HID==570)]=1
AMI$AMI09q[which(AMI$HID==575)]=1
AMI$AMI09q[which(AMI$HID==580)]=1
AMI$AMI09q[which(AMI$HID==590)]=1
AMI$AMI09q[which(AMI$HID==600)]=1
AMI$AMI09q[which(AMI$HID==610)]=1
AMI$AMI09q[which(AMI$HID==630)]=1
AMI$AMI09q[which(AMI$HID==640)]=1
AMI$AMI09q[which(AMI$HID==645)]=1
AMI$AMI09q[which(AMI$HID==650)]=1
AMI$AMI09q[which(AMI$HID==651)]=1

table(AMI10$Index, AMI10$HID)
AMI$AMI10q<-0
AMI$AMI10q[which(AMI$HID==50)]=1
AMI$AMI10q[which(AMI$HID==105)]=1
AMI$AMI10q[which(AMI$HID==155)]=1
AMI$AMI10q[which(AMI$HID==220)]=1
AMI$AMI10q[which(AMI$HID==280)]=1
AMI$AMI10q[which(AMI$HID==310)]=1
AMI$AMI10q[which(AMI$HID==340)]=1
AMI$AMI10q[which(AMI$HID==345)]=1
AMI$AMI10q[which(AMI$HID==347)]=1
AMI$AMI10q[which(AMI$HID==420)]=1
AMI$AMI10q[which(AMI$HID==430)]=1
AMI$AMI10q[which(AMI$HID==450)]=1
AMI$AMI10q[which(AMI$HID==460)]=1
AMI$AMI10q[which(AMI$HID==490)]=1
AMI$AMI10q[which(AMI$HID==540)]=1
AMI$AMI10q[which(AMI$HID==565)]=1
AMI$AMI10q[which(AMI$HID==570)]=1
AMI$AMI10q[which(AMI$HID==575)]=1
AMI$AMI10q[which(AMI$HID==580)]=1
AMI$AMI10q[which(AMI$HID==590)]=1
AMI$AMI10q[which(AMI$HID==610)]=1
AMI$AMI10q[which(AMI$HID==630)]=1
AMI$AMI10q[which(AMI$HID==640)]=1
AMI$AMI10q[which(AMI$HID==645)]=1
AMI$AMI10q[which(AMI$HID==650)]=1
AMI$AMI10q[which(AMI$HID==668)]=1
```

```
table(AMI11$Index, AMI11$HID)
AMI$AMI11q<-0
AMI$AMI11q[which(AMI$HID==50)]=1
AMI$AMI11q[which(AMI$HID==105)]=1
AMI$AMI11q[which(AMI$HID==120)]=1
AMI$AMI11q[which(AMI$HID==140)]=1
AMI$AMI11q[which(AMI$HID==155)]=1
AMI$AMI11q[which(AMI$HID==220)]=1
AMI$AMI11q[which(AMI$HID==280)]=1
AMI$AMI11q[which(AMI$HID==310)]=1
AMI$AMI11q[which(AMI$HID==340)]=1
AMI$AMI11q[which(AMI$HID==345)]=1
AMI$AMI11q[which(AMI$HID==347)]=1
AMI$AMI11q[which(AMI$HID==370)]=1
AMI$AMI11q[which(AMI$HID==390)]=1
AMI$AMI11q[which(AMI$HID==420)]=1
AMI$AMI11q[which(AMI$HID==430)]=1
AMI$AMI11q[which(AMI$HID==450)]=1
AMI$AMI11q[which(AMI$HID==460)]=1
AMI$AMI11q[which(AMI$HID==490)]=1
AMI$AMI11q[which(AMI$HID==540)]=1
AMI$AMI11q[which(AMI$HID==565)]=1
AMI$AMI11q[which(AMI$HID==570)]=1
AMI$AMI11q[which(AMI$HID==575)]=1
AMI$AMI11q[which(AMI$HID==580)]=1
AMI$AMI11q[which(AMI$HID==590)]=1
AMI$AMI11q[which(AMI$HID==600)]=1
AMI$AMI11q[which(AMI$HID==610)]=1
AMI$AMI11q[which(AMI$HID==630)]=1
AMI$AMI11q[which(AMI$HID==640)]=1
AMI$AMI11q[which(AMI$HID==645)]=1
AMI$AMI11q[which(AMI$HID==650)]=1
AMI$AMI11q[which(AMI$HID==668)]=1
write.csv(AMI, file="AMIq.csv", row.names=FALSE)
```

Appendix C

Data Variables and Descriptions

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
ADHOUR	Admission Hour	Num	3	00 12:00 - 12:59 Midnight 01 01:00 - 01:59 AM 02 02:00 - 02:59 AM 03 03:00 - 03:59 AM 04 04:00 - 04:59 AM 05 05:00 - 05:59 AM 06 06:00 - 06:59 AM 07 07:00 - 07:59 AM 08 08:00 - 08:59 AM 09 09:00 - 09:59 AM 10 10:00 - 10:59 AM 11 11:00 - 11:59 AM 12 12:00 - 12:59 Noon 13 01:00 - 01:59 PM 14 02:00 - 02:59 PM 15 03:00 - 03:59 PM 16 04:00 - 04:59 PM 17 05:00 - 05:59 PM 18 06:00 - 06:59 PM 19 07:00 - 07:59 PM 20 08:00 - 08:59 PM 21 09:00 - 09:59 PM 22 10:00 - 10:59 PM	The hour is in military format. For Quarter 4 2006 data, the ADHOUR variable is missing from approximately 3% of the records.

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
				23 11:00 - 11:59 PM 99 Hour Unknown	
ADMD	Admission Date	Num	8	SAS Date	For observation cases, the date the patient is actually admitted is the admission date.
ADMDAY	Admission Day of the week	Num	8	1 Sunday 2 Monday 3 Tuesday 4 Wednesday 5 Thursday 6 Friday 7 Saturday	
ADMMTH	Admission Month of the Year	Num	8		
ADMS	Admission Source	Char	1	1 Physician Referral 2 Clinic Referral 3 HMO Referral 4 Transfer from Hospital 5 Transfer from Skilled Nursing Facility 6 Transfer from Another Health Care Facility 7 Emergency Room 8 Court/Law Enforcement 9 Info Not Available A Transfer from Critical Access Hospital B Transfer from a HHA	If determining a person admitted through the ED, use CHG450 greater than zero. When ADM_TYPE equals ‘4’, use the Newborn Coding Structure.

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
				C Readmit to same HHA D Transfer from Hospital Inpatient in the Same Facility E Transfer from Ambulatory Surgery Center F Transfer from a hospice facility Newborn Coding Structure: 1 Normal Delivery 2 Premature Delivery 3 Sick Baby 4 Extramural Birth 5 Born in this Hospital 6 Born outside this Hospital	
ADMYEAR	Admission Year	Num	8		
ADM_DIAG	Admission Diagnosis	Char	6	ICD-9	
ADM_TYPE	Admission Type	Char	1	1 Emergency 2 Urgent 3 Elective 4 Newborn 5 Trauma Center Activation 6 – 8 Reserved National Assignment 9 N/A	
AGE	Patient Age	Num	5	Integer	Age at date of discharge.
AGRP	Patient Age Group	Num	3	1 Age less than 1 2 Age 01-04 3 Age 05-09	Patient Age Group

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
				4 Age 10-14 5 Age 15-19 6 Age 20-24 7 Age 25-29 8 Age 30-34 9 Age 35-39 10 Age 40-44 11 Age 45-49 12 Age 50-54 13 Age 55-59 14 Age 60-64 15 Age 65-69 16 Age 70-74 17 Age 75-79 18 Age 80-84 19 Age 85+	
DISD	Discharge Date	Num	8	SAS Date	
DISDAY	Discharge Day of the week	Num	8	1 Sunday 2 Monday 3 Tuesday 4 Wednesday 5 Thursday 6 Friday 7 Saturday	
DISDHR	Discharge Hour	Num	3	00 12:00 - 12:59 Midnight 01 01:00 - 01:59 AM 02 02:00 - 02:59 AM 03 03:00 - 03:59 AM 04 04:00 - 04:59 AM 05 05:00 - 05:59 AM	The hour is in military format.

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
				06 06:00 - 06:59 AM 07 07:00 - 07:59 AM 08 08:00 - 08:59 AM 09 09:00 - 09:59 AM 10 10:00 - 10:59 AM 11 11:00 - 11:59 AM 12 12:00 - 12:59 Noon 13 01:00 - 01:59 PM 14 02:00 - 02:59 PM 15 03:00 - 03:59 PM 16 04:00 - 04:59 PM 17 05:00 - 05:59 PM 18 06:00 - 06:59 PM 19 07:00 - 07:59 PM 20 08:00 - 08:59 PM 21 09:00 - 09:59 PM 22 10:00 - 10:59 PM 23 11:00 - 11:59 PM 99 Hour Unknown	
DISMTH	Discharge Month of the Year	Num	8		
DISYEAR	Discharge Year	Num	8		
DISP	Discharge Status	Num	3	Appendix P	
DOB	Patient Date Of Birth	Num	8	SAS Date	
DRG4	Diagnosis Related Group	Num	4	CMS-DRG Version 24	100% of Inpatient Records are coded.

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
ER	Emergency Room Flag	Num	3	.=Inpatient 1=Emergency Room Visit	
HID	Hospital ID	Num	5	Appendix A: Hospital ID Table	
ID	Ors Assigned Tracking #	Num	8	Encrypted Individual Tracking #	
LBEDGRP	Bed Size based on Licensed Beds	Char	1	1 < 100 2 101-299 3 300+	
LOSD1	Length Of Stay	Num	5	Integer	Number of Days
MDC	Major Diagnostic Category	Num	8	Valid Code Range: 1 – 25. Appendix I: Major Diagnostic Categories.	
MED_NO	Medical Record Number	Char	17		
MSDRG	MS-DRG	Num	8	Starts October 2007 w/ Version 25	
OP	Outpatient Surgery Flag	Num	3		Only when imaging and outpatient surgery are in same file.
PAT_NO	Patient Number	Char	20		Facility-assigned patient identifier
PAYOR1	Primary Payor	Num	3	Appendix L: Payor Code Table	
PCODE	Surgery coding methodology	Num	8	1=ICD-9, 2=ICD-10	
PDATE	Primary Day of Surgery	Num	1		In relation to admission date
PDIAG	Primary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
PECODE	Cause Of Injury Code	Char	6	E800 – E869 and E877 – E999 Refer to the ICD-9-CM Coding Manual, Supplementary Classification of Injury and Poisoning.	An E-code is required when the primary diagnosis is an injury (Dx 800 – 959).

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
PPOA	Primary Present on Admission	Char	1	Y=Yes, N=No, U=No Information, W=Clinically Undetermined 1,E,(Blank)=Exempt	
PPROC	Primary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual, Procedure Tabular.	Approximately 40% of the records do not have a primary procedure.
PPROCD	Primary Procedure Date	Num	8	SAS date	
RACE	Patient Race	Num	3	. Missing 1 White 2 African-American 3 Asian 4 American Indian 5 Other 6 Hispanic	
SDATE1-SDATE12	Secondary Day of Surgery	Num	3		Day in relation to admission date.
SDIAG1	1st Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG2	2nd Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG3	3rd Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG4	4th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG5	5th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG6	6th Secondary	Char	6	001 – 999 ; V01 – V829	

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
	Diagnosis			Refer to the ICD-9-CM Coding Manual.	
SDIAG7	7th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG8	8th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG9	9th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG10	10th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG11	11th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG12	12th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG13	13th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SDIAG14	14th Secondary Diagnosis	Char	6	001 – 999 ; V01 – V829 Refer to the ICD-9-CM Coding Manual.	
SECODE	Place Of Occurrence Injury Code	Char	6	E8490 Home E8491 Farm E8492 Mine/Quarry E8493 Industrial Place and Premises E8494 Place for Recreation and Sport E8495 Street and Highway E8496 Public Building E8497 Residential Institution E8498 Other Specified Places	Place of Occurrence Code is not required for all E-Codes.
SEX	Gender Of Patient	Char	1	M = Male F = Female U = Unknown	

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
SPC1	1st Physician Specialty	Char	3	Appendix C.1: Physician Specialty Codes	
SPC2	2nd Physician Specialty	Char	3	Appendix C.1: Physician Specialty Codes	
SPC3	3rd Physician Specialty	Char	3	Appendix C.1: Physician Specialty Codes	
SPOA1-SPOA14	Secondary Present on Admissions	Char	1	Y=Yes, N=No, U=No Information, W=Clinically Undetermined 1,E,(Blank)=Exempt	
SPROC1	1st Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	Approximately 66% of the records do not have a 1st secondary procedure.
SPROC1D	1st Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC1.
SPROC2	2nd Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC2D	2nd Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC2.
SPROC3	3rd Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC3D	3rd Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC3.
SPROC4	4th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	.
SPROC4D	4th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC4.

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
SPROC5	5th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC5D	5th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC5.
SPROC6	6th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC6D	6th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC6.
SPROC7	7th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC7D	7th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC7.
SPROC8	8th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC8D	8th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC8.
SPROC9	9th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC9D	9th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC9.
SPROC10	10th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC10D	10th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC10.
SPROC11	11th Secondary	Char	7	01 - 9999	

Variable Name (for non-ASC11)	Data Element	Type	Length	Values	Comments
	Procedure			Refer to the ICD-9-CM Coding Manual.	
SPROC11D	11th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC11.
SPROC12	12th Secondary Procedure	Char	7	01 - 9999 Refer to the ICD-9-CM Coding Manual.	
SPROC12D	12th Secondary Procedure Date	Num	8		Completion of this field is directly related to SPROC12.
TRLVL	Trauma level	Num	3	Appendix N – Trauma levels	Completion of this field is directly related to SPROC12.
TSTAT	Teaching Status	Char	1	T Teaching Hospital N Non-Teaching Hospital	
URSTAT	Urban Rural Status	Char	1	U Urban R Rural	Based on MSA
ZIP	Patient Zip Code	Char	9	Digits 1-5	Based on patients mailing address

Appendix C.1 – Physician Specialty Codes
(FLAGSPC1, FLAGSPC2, FLAGSPC3)

089	A	Allergy
080	AD	Administrative Medicine
090	ADL	Adolescent Medicine
0AV	ADM	Addiction Medicine
0BA	ADP	Addiction Psychiatry
002	AI	Allergy And Immunology
0LL	ALI	Allergy & Immunology/Clinical And Laboratory Immunology
001	AM	Aerospace Medicine
003	AN	Anesthesiology
0MM	APM	Pain Management (Anesthesiology)
056	AS	Abdominal Surgery
085	ATP	Anatomic Pathology
000	BBK	Blood Banking/Transfusion Medicine
0BC	CBG	Clinical Biochemical Genetics
0PP	CCA	Critical Care Medicine (Anesthesiology)
0BD	CCG	Clinical Cytogenetics
092	CCM	Critical Care Medicine (Internal Medicine)
0QQ	CCP	Pediatric Critical Care Medicine
0GG	CCS	Surgical Critical Care (Surger)
005	CD	Cardiovascular Disease
057	CDS	Cardiovascular Surgery
0CE	CE	Cardiac Electrophysiology
0BE	CG	Clinical Genetics
025	CHN	Child Neurology
044	CHP	Child & Adolescent Psychiatry
036	CLP	Clinical Pathology
0BF	CMG	Clinical Molecular Genetics
0SS	CN	Clinical Neurophysiology
058	CRS	Colon & Rectal Surgery
	CTS	Cardio Thoracic Surgery
006	D	Dermatology
0TT	DDL	Clinical And Laboratory Dermatological Immunology

013	GPM	General Preventive Medicine
059	GS	General Surgery
015	GYN	Gynecology
016	HEM	Hematology (Internal Medicine)
0BT	HEP	Hepatology
0WW	HMP	Hematology (Pathology)
061	HNS	Head & Neck Surgery
	HO	Hemotologist/Oncologist
0XX	HSO	Hand Surgery (Orthopedic Surgery)
0YY	HSP	Surgery of the Hand (Plastic Surgery)
060	HSS	Surgery Of The Hand (Surgery)
018	ID	Infectious Disease
071	IG	Immunology
0AB	ILI	Clinical And Laboratory Immunology (Internal Medicine)
019	IM	Internal Medicine
0AC	IMG	Geriatric Medicine (Internal Medicine)
0BI	ISM	Sports Medicine (Internal Medicine)
021	LM	Legal Medicine
087	MFM	Maternal & Fetal Medicine
0II	MG	Medical Genetics
098	MM	Medical Microbiology
	MPD	Internal Medicine/Pediatrics
024	N	Neurology
0AD	NCC	Critical Care Medicine (Neurological Surgery)
0DD	NEO	Neo-Natal
023	NEP	Nephrology
027	NM	Nuclear Medicine
026	NP	Neuropathology
084	NPM	Neonatal-Perinatal Medicine

0KK	OSS	Orthopedic Surgery of the Spine
033	OT	Otology
074	OTO	Otolaryngology
0AL	OTR	Orthopedic Trauma
043	P	Psychiatry
041	PA	Clinical Pharmacology
	PCC	Pulmonary Critical Care
0AM	PCH	Chemical Pathology
0AN	PCP	Cytopathology
038	PD	Pediatrics
039	PDA	Pediatric Allergy
040	PDC	Pediatric Cardiology
0AA	PDE	Pediatric Endocrinology
	PDI	Pediatric Infectious Disease
0BJ	PDO	Pediatric Otolaryncology
0FF	PDP	Pediatric Pulmonology
051	PDR	Pediatric Radiology
064	PDS	Pediatric Surgery
0BK	PDT	Medical Toxicology(Pediatrics)
	PE	Pediatric Emergency Medicine
0HH	PEM	Pediatric Emergency Medicine
0AO	PG	Pediatric Gastroenterology
047	PH	Public Health and General Prevention Medicine
082	PHO	Pediatric Hematology/Oncology
0AP	PIP	Immunopathology
0AQ	PLI	Clinical And Laboratory Immunology (Pediatrics)
042	PM	Physical Medicine and Rehabilitation
0BL	PMD	Pain Medicine
083	PN	Pediatric Nephrology
0BM	PO	Pediatric Ophthalmology
0BU	PP	Pediatric Pathology
0BN	PPR	Pediatric Rheumatology
065	PS	Plastic Surgery
0BO	PSM	Sports Medicine (Pediatrics)
035	PTH	Anatomic/Clinical Pathology

007	DIA	Diabetes
094	DLI	Diagnostic Laboratory/Immunology
095	DMP	Dermatopathology
050	DR	Diagnostic Radiology
008	EM	Emergency Medicine
009	END	Endocrinology, Diabetes And Metabolism
0LG	ESM	Sports Medicine (Emergency Medicine)
0BH	ETX	Medical Toxicology (Emergency Medicine)
037	FOP	Forensic Pathology
010	FP	Family Practice
0UU	FPG	Geriatric Medicine (Family Practice)
096	FPS	Facial Plastic Surgery
0VV	FSM	Sports Medicine (Family Practice)
011	GE	Gastroenterology
014	GER	Geriatrics
086	GO	Gynecological Oncology
012	GP	General Practice
	OST	Osteopathy
	USA	US Army
	AF	US Air Force

099	NR	Nuclear Radiology
062	NS	Neurological Surgery
0AF	NSP	Pediatric Surgery (Neurology)
028	NTR	Nutrition
0AG	OAR	Adult Reconstructive Orthopedics
030	OBG	Obstetrics & Gynecology
029	OBS	Obstetrics
0AH	OCC	Critical Care Medicine (Obstetrics & Gynecology)
031	OM	Occupational Medicine
0AI	OMO	Musculoskeletal Oncology
073	ON	Medical Oncology
0AJ	OP	Pediatric Orthopedics
032	OPH	Ophthalmology
063	ORS	Orthopedic Surgery
069	OS	Other Specialty (Physician designated a specialty other than appearing here)
0AK	OSM	Sports Medicine (Orthopedic Surgery)
	USN	US Navy
	PHS	US Public Health Service

0BP	PTX	Medical Toxicology (Preventive Medicine)
048	PUD	Pulmonary Diseases
045	PYA	Psychoanalysis
0JJ	PYG	Geriatric Psychiatry
049	R	Radiology
088	REN	Reproductive Endocrinology
053	RHU	Rheumatology
0BB	RIP	Radioisotopic Pathology
0BQ	RNR	Neuroradiology
0EE	RO	Radiation Oncology
0BR	RP	Radiological Physics
081	SH	Student Health
	SM	Sleep Medicine
	SO	Surgical Oncology
052	TR	Therapeutic Radiation
067	TRS	Traumatic Surgery
066	TS	Thoracic Surgery
	TTS	Transplant Surgery
068	U	Urology
0AT	UM	Undersea Medicine
0BS	UP	Pediatric Urology
0AU	VIR	Vascular And Interventional Radiology
0CC	VS	General Vascular Surgery

Note: No code appears for those physicians who have not designated a practice specialty. The code fix appears for those physicians in a transitional year of accredited graduate medical education.

An asterisk (*) preceding a Type of Practice indicates the physician is currently in a residency training program.

An asterisk (*) following a Type of Practice indicates the physician has been certified by one of the American Board of Medical Specialties. Current certification information should be obtained directly from the physician.

The information supplied by each physician on the type of practice is interpreted from the physician's annual re-registration application. The Board has not verified the specific amount of post-graduate training in this area of practice. The information on the type of practice is not to be used by any third party to determine specialty status. This information should be obtained from the physician.

Appendix C.2 – Major Diagnostic Categories
(MDC)

01	Diseases of the Nervous System	14	Pregnancy, Childbirth, Puerperium
02	Diseases and Disorders of the Eye	15	Newborns, Other Neonates
03	Ear, Nose, Mouth, and Throat	16	Blood and Blood Forming Organs
04	Respiratory System	17	Myeloproliferative Diseases
05	Circulatory System	18	Infectious and Paras. Diseases
06	Diseases of the Digestive System	19	Mental Diseases and Disorders
07	Hepatobiliary System and Pancrease	20	Alcohol/Drug Use, Induc. Organ.
08	Musculoskeletal System	21	Injuries, Poisonings, Toxic
09	Skin, Subcutaneous Tissue, Breast	22	Burns
10	Endocrine, Nutritional, Metabolic	23	Factors Infl. Health Status
11	Kidney and Urinary Tract	24	Multiple Significant Trauma
12	Male Reproductive System	25	Human Immunodeficiency Virus
13	Female Reproductive System	Other	Unknown Diagnosis Code

Appendix C.3 – Payor
(PAYOR)

1	Self Pay
2	Medicare
3	Medicaid
4	Commercial Ins.
5	Worker's Compensation
6	Indigent/Charitable Organization
7	Other Government(Champus,State,County)
8	HMO
9	Not Stated

Appendix C.4 – Trauma Levels

Taken from the "2005 South Carolina Health Plan"

South Carolina Sate Health Planning Committee & SC Department of Health and Environmental Control

Level I:

The highest level of capability available. Generally speaking, this hospital has to have general surgery capability in-house at all times. Anesthesia capabilities are required to be in-house at all times, but this requirement may be met with CRNA's or anesthesiology chief residents. Orthopedic surgery, neurological surgery, and other surgical and medical specialties must be immediately available. Generally, these trauma centers will be attached to medical schools or will have residency programs because of the in-house requirements, since fourth year and senior trauma residents can help meet the requirements of the level I criteria. The Level I Trauma Center also has the responsibility of providing education and outreach programs to other area hospitals and the public and must also conduct trauma-related research.

Level II:

This trauma center has extensive capability and meets the needs of most trauma victims. It is required to have general, neurologic, and orthopedic surgery available when the patient arrives. Anesthesia capabilities are required to be in-house at all times, but this requirement may be met with CRNA's. Other surgical and medical specialties are required to be on-call and promptly available. These hospitals may develop local procedures for the surgeon being available in the Emergency Department when the patient arrives. The major difference between Level I and Level II facilities is that the major surgical specialties are allowed to be on-call but with the clear commitment to be in the Emergency Department when the patient arrives. Level II hospitals do not have the research requirements of a Level I trauma Center.

Level III:

These Hospitals are committed to caring for the trauma patient. Level III trauma centers can provide prompt assessment, resuscitation, emergency operations, and stabilization, and also arrange for possible transfer to a facility that can provide definitive trauma care. These hospitals are required to have general surgery, anesthesia, and internal medicine on-call and promptly available. The general surgeon is required to be on-call and promptly available in the Emergency Department as the trauma team leader.

Appendix C.5 – Patient Discharge Status
(DISP)

01	Discharged to home or self care (routine discharge)
02	Discharged/transferred to a short term general hospital for inpatient care
03	Discharged/transferred to skilled nursing facility (SNF) w/ Medicare certification
04	Discharged/transferred to an intermediate care facility (ICF)
05	Discharged/transferred to a non-Medicare PPS children's hospital or non –Medicare PPS cancer hospital for inpatient care
06	Discharged/transferred to home under care of organized home health service organization
07	Left against medical advice or discontinued care
08	Discharged/transferred to home under care of a Home IV provider
09	Admitted as an inpatient to this hospital
10 – 19	Reserved for National Assignment
20	Expired
21	Effective 10/1/2009 – Dishcarged/transferred to court/law enfocement
22 – 29	Reserved for National Assignment
30	Still patient
31 – 39	Reserved for National Assignment
40	Expired at home
41	Expired in a medical facility, e.g. hospital, SNF, ICF, or free standing Hospice
42	Expired – place unknown
43	Discharged/transferred to a federal health care facility
44 – 49	Reserved for National Assignment
50	Hospice – home
51	Hospice – medical facility
52 – 60	Reserved for National Assignment
61	Discharged/transferred to hospital based Medicare approved swing bed w/in the hospital's approved swing bed arrangement
62	Discharge/transferred to an inpatient rehabilitation facility (IRF) including rehabilitation distinct part units of a hospital
63	Discharged/transferred to a Medicare certified long term care hospital (LTCH)
64	Discharged/transferred to a nursing facility certified under Medicaid but not certified under Medicare
65	Discharged/transferred to a psychiatric hospital or psychiatric distinct part unit of a hospital
66	Discharged/transferred to a Critical Access Hospital (CAH)
67-69	Reserved for assignment by the NUBC
70	Discharged/transferred to another type of health care institution not defined elsewhere in this code list (see code 05)
71-99	Reserved for assignment by the NUBC

Appendix D

Correlation Coefficients for Table 5.1 Odds Ratios and 95% Confidence Intervals for 30-Day AMI Readmissions

Correlation Coefficients among independent variables for the Logistic Regression

	Female	Self-Payer	Medicare	Medicaid	Commercial Insurance	Indigent	White	Black	Teaching Hospital
Female	1.000								
Self-Payer	-0.012	1.000							
Medicare	0.047	-0.250	1.000						
Medicaid	0.045	-0.072	-0.072	1.000					
Commercial Insurance	-0.031	-0.427	-0.423	-0.122	1.000				
Indigent	-0.014	-0.155	-0.154	-0.045	-0.263	1.000			
White	-0.090	-0.054	-0.064	-0.047	0.090	-0.016	1.000		
Black	0.102	0.044	0.074	0.053	-0.089	0.014	-0.917	1.000	
Teaching Hospital	-0.004	-0.063	0.030	0.015	-0.041	0.126	-0.006	0.015	1.000

Appendix E

Hospital Readmission Rate and Percentage Poor Data

Hospital Readmission Data for the 48 Analyzed Hospitals

Hospital ID	AMI Admissions	AMI Readmission	Readmission Rate	Percentage Poor*
Non-Teaching 1	38	1	2.63	9.66
Non-Teaching 2	33	2	6.06	11.15
Non-Teaching 3	73	5	6.85	6.04
Non-Teaching 4	58	4	6.9	13.09
Non-Teaching 5	42	3	7.14	15.64
Non-Teaching 6	96	7	7.29	8.07
Non-Teaching 7	68	5	7.35	4.74
Non-Teaching 8	63	5	7.94	5.28
Non-Teaching 9	71	6	8.45	21.26
Non-Teaching 10	59	5	8.47	21.51
Non-Teaching 11	64	6	9.38	5.51
Non-Teaching 12	62	6	9.68	8.52
Non-Teaching 13	121	12	9.92	13.27
Non-Teaching 14	196	21	10.71	10.55
Non-Teaching 15	476	53	11.13	12.19
Non-Teaching 16	71	8	11.27	20.72
Non-Teaching 17	190	22	11.58	9.66
Non-Teaching 18	120	14	11.67	15.84
Non-Teaching 19	111	13	11.71	13.96
Non-Teaching 20	129	16	12.4	7.7

*Percentage of poor is defined as the sum of Medicaid and Indigent patients divided by total patients at that hospital.

Appendix E Continued

Hospital ID	AMI Admissions	AMI Readmission	Readmission Rate	Percentage Poor*
Non-Teaching 21	160	20	12.5	5.53
Non-Teaching 22	135	17	12.59	10.81
Non-Teaching 23	265	37	13.96	12.87
Non-Teaching 24	78	11	14.1	9.49
Non-Teaching 25	184	26	14.13	8.02
Non-Teaching 26	40	6	15	11.94
Non-Teaching 27	178	28	15.73	7.07
Non-Teaching 28	211	35	16.59	9.57
Non-Teaching 29	30	5	16.67	21.19
Non-Teaching 30	150	25	16.67	15.99
Non-Teaching 31	418	78	18.66	7.74
Non-Teaching 32	528	100	18.94	10.91
Non-Teaching 33	1476	281	19.04	6.75
Non-Teaching 34	631	121	19.18	9.91
Non-Teaching 35	165	32	19.39	20.02
Non-Teaching 36	115	23	20	4.92
Non-Teaching 37	179	38	21.23	11.31
Non-Teaching 38	423	104	24.59	8.44
Non-Teaching 39	290	77	26.55	7.69
Non-Teaching 40	497	140	28.17	13.38

*Percentage of poor is defined as the sum of Medicaid and Indigent patients divided by total patients at that hospital.

Appendix E Continued

Hospital ID	AMI Admissions	AMI Readmission	Readmission Rate	Percentage Poor*
Teaching 1	68	9	13.24	15.68
Teaching 2	397	65	16.37	7.52
Teaching 3	971	199	20.49	12.8
Teaching 4	736	155	21.06	21.55
Teaching 5	1412	323	22.88	21.42
Teaching 6	1003	237	23.63	11.06
Teaching 7	457	109	23.85	9.96
Teaching 8	455	110	24.18	8.87

*Percentage of poor is defined as the sum of Medicaid and Indigent patients divided by total patients at that hospital.

Appendix F

Two Methods for Estimating Average Reference Readmission Rates And Percentage Poor Patients

Comparison of Hospital Average Readmission Rate and Weighted Hospital Average Readmission Rate By Overall Total and Quintile

Grouping	Average Rate	Weighted Average Rate*	Percentage Poor Patients**
Total	14.75%	19.03%	11.60%
Quintile 1	12.80%	16.89%	5.63%
Quintile 2	16.84%	20.38%	8.28%
Quintile 3	14.58%	19.43%	10.32%
Quintile 4	14.57%	18.29%	13.05%
Quintile 5	14.98%	20.20%	19.52%

*Weighted average rate weights each hospital AMI readmission rate by the number of AMI patients admitted to each hospital relative to the overall total or quintile total. **Percentage poor patients is the percentage of indigent and Medicaid patients admitted for AMI relative to all AMI patients served by hospitals in each quintile and overall total.

Appendix G

Bootstrapping Sample Code

Let h_i serve as placeholder for identification of each of the 48 hospitals. h_i -> h_n where n=48

```
h_i <- rbinom(1, (h_i Sample size), (h_i readmission rate))
theta. h_i.ra<-function(h_i){rbinom(1, (h_i Sample size), (h_i readmission rate))}
boot. h_i.ra<-bootstrap(h_i, 1000, theta. h_i.ra)
CI h_i <-binom.confint(boot. h_i.ra$thetastar, (h_i Sample size), conf.level = 0.95,
method="exact")
N=nrow(CI h_i)
CI h_i$X<-(1:N)
CI h_i$Hosp<-" h_i "
CI h_i$HID<-paste(CI h_i $Hosp, CI h_i $X, sep=".")


#aggregate all boostraps
data<-rbind(CI h_i, ...., CI h_n )

#sort by bootstrap iteration X, where X[1:1000]
datasort<-data[order(data$X),]


#Create 1,000 unique p̂ to determine excess readmission rates
pctra <- with(datasort,
        by(datasort, datasort$X,
          function(datasort) phat<-(sum(datasort$x)/sum(datasort$n))))
pctra
RA<-t(sapply(pctra, I))
RA<-as.data.frame(RA)


#Attach the 1,000 p̂ to each hospital for determination of excess readmission
data1<-merge(data, RA, by="X", all.x=T)
data1sort<-data1[order(data1$X,data1$HID),]


#Repeat above analysis for each quintile
datasort<-data[order(data$quintile),]
pctra.quint <- with(datasort,
          by(datasort, datasort$quintile,
            function(datasort) phat.quint <-(sum(datasort$x)/sum(datasort$n))))
```

Appendix G continued

```
pctra.quint
RA.quint <-t(sapply(pctra.quint, I))
RA.quint <-as.data.frame(RA1.quint)
```

Appendix H

Logistic Regression Code

R Code for logistic Regression including age

```
summary(model1<-glm(RA ~ AGE + female + PAY.SELF + PAY.CARE + PAY.CAID
+ PAY.COMINS  + PAY.INDIGENT + WHITE +  BLACK  +  as.factor(TSTAT),
data=ami, family=binomial(logit)))
summary(model1)
exp(coef(model1))
exp(confint(model1))
```

R Code for logistic Regression excluding age

```
summary(model2<-glm(RA ~  female + PAY.SELF + PAY.CARE + PAY.CAID +
PAY.COMINS
              + PAY.INDIGENT + WHITE +  BLACK  +  as.factor(TSTAT)
              , data=ami, family=binomial(logit)))
summary(model2)
exp(coef(model2))
exp(confint(model2))
```

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